PL-TR-97-2090

INITIAL REGIONALIZATION EFFORTS FOR THE IMS SEISMIC NETWORK

Steven Bottone
Mark D. Fisk
Gary D. McCartor
Richard J. Carlson

Mission Research Corp
735 State Street
P.O. Drawer 719
Santa Barbara, CA 93102-0719

15 March 1997

Scientific Report No. 3

PHILLIPS LABORATORY
Directorate of Geophysics
AIR FORCE MATERIEL COMMAND
HANSCOM AFB, MA 01731-3010

SPONSORED BY
Advanced Research Projects Agency (DoD)
Nuclear Monitoring Research Office
ARPA ORDER No. C-325

MONITORED BY
Phillips Laboratory
CONTRACT No. F19628-95-C-0101

The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either express or implied, of the Air Force or the U.S. Government.

This technical report has been reviewed and is approved for publication.

Claire A. Marcotte

CLAIRE A. MARCOTTE
PL/GP R&D Contracts Liaison

Charles P. Pike

CHARLES P. PIKE, Director
Business Management Division

This report has been reviewed by the ESC Public Affairs Office (PA) and is releasable to the National Technical Information Service (NTIS).

Qualified requestors may obtain additional copies from the Defense Technical Information Center. All others should apply to the National Technical Information Service.

If your address has changed, or if you wish to be removed from the mailing list, or if the addressee is no longer employed by your organization, please notify PL/IM, 29 Randolph Road, Hanscom AFB, MA 01731-3010. This will assist us in maintaining a current mailing list.

Do not return copies of this report unless contractual obligations or notices on a specific document require that it be returned.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB NO. 0704.0188*

1. AGENCY USE ONLY *(Leave Blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	15 Mar 1997	Scientific Report No. 3

4. TITLE AND SUBTITLE
Initial Regionalization Efforts for the IMS Seismic Network

5. FUNDING NUMBERS
Contract F19628-95-C-0101
PE 62301E
PR NM95 TA GM WU AA

6. AUTHOR(s)
Steven Bottone, Gary D. McCartor*
Mark D. Fisk, Richard J. Carlson

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Mission Research Corporation
735 State Street, P. O. Drawer 719
Santa Barbara, CA 93102-0719

8. PERFORMING ORGANIZATION REPORT NUMBER
MRC-R-1539

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Phillips Laboratory
29 Randolph Road
Hanscom Air Force Base, MA 01731-3010
PL/GP R&D Contracts Liaison: Claire Marcotte

10. SPONSORING/MONITORING AGENCY REPORT NUMBER
PL-TR-97-2090

11. SUPPLEMENTARY NOTES

* Department of Physics, Southern Methodist University, Dallas, TX
This research was partially supported under contract F19628-95-C-0098 with Southern Methodist University.

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public distribution;
distribution unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*

In this report, initial efforts are described to establish regional training sets and region-specific distance corrections, for use in seismic event characterization, for 35 Primary and 51 Auxiliary seismic stations of the International Monitoring System (IMS) network. Seismic data considered include Pn/Lg and Pn/Sn in the 2–4 Hz, 4–6 Hz, and 6–8 Hz bands for 2797 regional events collected over a 16-month period at the Prototype International Data Centre (PIDC). Regional training sets for each station consist of the discriminant values for events above mb 3.5 (to minimize potential contamination by mining blasts), within 20 degrees from the station, and with signal-to-noise ratios greater than 1.5. Empirical distance corrections are computed for and applied to each discriminant in each training set separately. Events in the training sets which are determined to be outliers, using a generalized likelihood ratio test, are removed and the distance corrections are iteratively re-computed. The training sets for each station are then categorized in terms of their utility for experimental evaluation of event characterization capabilities at the PIDC. Last, future planned efforts to continue improving the initial region-specific distance corrections and training sets are described.

14. SUBJECT TERMS
Seismic Event Characterization; Comprehensive Test Ban
Regional Training Sets; International Monitoring System
Distance Corrections; International Data Centre

15. NUMBER OF PAGES
50

16. PRICE CODE

17. Security CLASSIFICATION OF REPORT	18. Security CLASSIFICATION OF THIS PAGE	19. Security CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	SAR

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18
298-102

CLASSIFIED BY:

DECLASSIFY ON:

Table of Contents

List of Figures

List of Tables

1. Introduction

Seismic signals observed at regional distances are generally quite complicated and often exhibit dramatic dependence on regional variations. Hence, region-specific information regarding regional seismic discriminants is vital in distinguishing nuclear explosions from other events. Unfortunately, relevant ground-truth data, particularly for underground nuclear explosions, do not exist for most regions. Also, it has yet to be shown that a discrimination threshold, established in a region for which data exist, can be transported effectively to a new region. Thus, in most cases, screening of regional seismic events, within the context of monitoring the Comprehensive Nuclear Test-Ban Treaty (CTBT), is a problem of identifying unusual events (i.e., outliers) relative to routine seismic activity in their respective regions.

Fisk et al. (1993, 1994, 1995, 1996b) describe the outlier (or regional population) analysis and provide numerous results of applications to regional seismic data sets for diverse geological regions, for a wide range of epicentral distances and magnitudes, and for single stations and arrays. Software to perform the regional population analysis has been installed at the Prototype International Data Centre (PIDC) in Arlington, VA (e.g., Fisk et al., 1996a). For operational use in screening regional seismic events, regional training sets must be established for comparison. As Fisk et al. (1994, 1995, 1996b) and others have noted, regional discriminants must be corrected for distance- and frequency-dependent attenuation in order to obtain valid results. Furthermore, evidence suggests that significant tectonic variations may require subregional training sets and distance corrections.

In this report, we describe our initial efforts to establish regional event-characterization training sets and distance corrections for 35 Primary and 51 Auxiliary seismic stations of the International Monitoring System (IMS) network. These IMS stations were providing regular data to the PIDC as of January 1997. Section 2 provides some technical background on the outlier approach and empirical distance corrections. Section 3 describes the IMS seismic data used in this work. In Section 4 we compute distance corrections for Pn/Lg and Pn/Sn in several frequency bands, based on the regional training sets for each IMS station with sufficient data. Section 5 discusses the discriminant distributions and outlier removal, in order to iteratively refine the distance corrections. In Section 6 we categorize each station in terms of the status of the initial training sets and distance corrections for experimental operational use at the PIDC. While there are many stations with adequate data over a relatively broad range of regional distances, for which reasonable initial distance corrections can be established, there are many stations which require further data and subregional analyses. Section 7 provides some conclusions and recommendations as to the status and future direction of our regionalization efforts.

2. Overview of Technical Approach

To assess whether an event is an outlier relative to the event population in its respective region, a comparison is made to a training set. A training set consists of a sample of regional discriminants for events in the same region (defined for now to be within 20 degrees from a given station) as the event to be tested. Ideally, a training set would consist of events of known type, with ground truth, which have the same location and magnitude as the event being tested. In reality, however, such events are not available in sufficient numbers to afford this luxury. Therefore, events with different locations and magnitudes must be used in the same training set, leading to the necessity of "correcting" the measured values of the discriminants so the training events can be interpreted as coming from the "same" population as the event being tested.

In most practical situations we will not know the event types, *a priori*. A fundamental assumption is made that the number of new nuclear tests in a region will be relatively small compared to the number of other types of events in the region. Also, since there only are a relatively small number of mining blasts that occur above mb 3.5, due to typical mining practices, the majority of regional events above this magnitude level consist of earthquakes. Hence, the primary concern for monitoring above this level is to distinguish potential nuclear explosions from respective regional earthquake populations. We focus on this case here. (Fisk et al., 1993, 1994, also considered cases in which earthquake training sets were contaminated by large quarry blasts or rock bursts.)

Meaningful application of the outlier analysis requires a second fundamental assumption, i.e., that there is at least one regional discriminant that, when appropriately corrected for relevant geophysical effects (e.g., distance dependence), provides some distinguishing measure of earthquakes and simple explosions. It is not necessary to know, *a priori*, what the quantitative value of the separation is, only that the discriminant(s) will provide some separation. In other words, the outlier analysis cannot provide meaningful results in the absence of useful discriminants, but does provide a robust methodology to treat multivariate data for the purpose of quantifying anomalous events, including nuclear explosions, if such discriminants exists.

The regional event characterization parameters considered here consist of ratios of maximum phase amplitude measurements, Pn/Lg and Pn/Sn in the 2–4 Hz, 4–6 Hz, and 6–8 Hz bands. In many cases, the events have missing data; one or more of the discriminants may be missing due to blockage or strong attenuation of a particular seismic phase or poor signal-to-noise, for example. It is also possible for a seismic event under consideration to have regional measurements at more than one station. In such a case it is possible to use events with regional discriminants measured at all of these stations to compose the training set. The multi-station case will be considered in the future. Here we restrict our study to training sets with regional measurements at one station only.

In practice, then, there is one training set for each station in the network. Events with at least one measurement of the six discriminants listed above are candidates for the training sets. To prevent possible contamination by mining blasts, only events above mb 3.5 are considered. Only those of the six discriminants with SNR greater than 1.5 are included in a training set. As more data become available, a more restrictive SNR cut-off may be used.

An outlier can be thought of as a measurement that is inconsistent with the measurements of some set of data, in our case, the training set. It is useful to hypothesize that the data set consists of random samples from some (unknown) distribution. Typically, the distribution is of the continuous type, with all (in our case, positive) values possible as an outcome of a measurement. If this is the case, then a candidate outlier, whether a random sample from a different distribution or the same distribution of the training set, will have values which are possible values of the training set distribution. In this case, the outlier must be defined as a point (in the six-dimensional space of discriminant values) that is "far" from the center of the training set distribution, i.e., in regions of low probability. In the univariate case, "far" means either a large or small discriminant value relative to the mean, as compared to the variance. In the multivariate case, low probability regions are much more complicated, involving the correlations of the discriminants.

Assuming normality of the discriminant distributions and using a generalized likelihood ratio test, Fisk et al. (1993, 1994, 1995, 1996b) have shown how specifying low probability regions can be quantified. As explained in more detail by Fisk et al. (1996b), an outlier is defined as a set of discriminant values which yield a value of the generalized likelihood ratio, λ, that is less than a threshold, λ_α. The threshold, λ_α, is set such that $P[\lambda < \lambda_\alpha | H_0] = \alpha$, when it is true that the event being tested actually belongs to the event population (i.e., when the null hypothesis, H_0, is true), where α is the significance level of the test. That is, if the six values were a sample from the training set distribution, then only $100\alpha\%$ of the time is the value λ less than λ_α. Events with likelihood ratios less than the threshold are considered outliers at the specified significance level. We typically set $\alpha = 0.01$. The statistic, λ, combines multivariate discriminant data for the event being tested and the training events into a univariate expression. It provides a useful metric with which to perform a hypothesis test or to rank events. The latter provides an alternative to imposing a rigid "yes/no" judgement and a means to focus on the most anomalous events.

In order for the outlier test to provide meaningful results, each event in the training set should be a sample from the same distribution. However, the events that make up a given training set will have occurred at various locations, in different tectonic subregions, and have propagation paths with different geophysical effects on the observed regional signals. In particular, events will have different distances from the station. Since the various phases (Pn, Lg, Sn) exhibit different rates of

attenuation, the ratios Pn/Lg and Pn/Sn vary with epicentral distance. From a statistical perspective, these effects can lead to events in a given training set being described by possibly different distributions, with different means and covariance matrices, than other events in the training set at different locations. From a geophysical or monitoring perspective, these effects, if left untreated, can lead to inaccurate screening or identification results, i.e., potential missed violations. Fisk et al. (1994, 1996b) discuss cases, including a Lop Nor nuclear explosion, in which events would be misidentified if distance corrections were not applied to the discriminants.

It is also possible that the discriminant distributions depend on magnitude. However, evidence suggests that linearity is a good approximation, so that the Pn/Lg and Pn/Sn discriminants do not exhibit significant dependence on magnitude. Thus, it will be assumed in this study that the effect of magnitude on the distribution of regional amplitude ratios is negligible relative to distance and other path effects.

Here we focus on the effect of epicentral distance on regional discriminants and leave other considerations for future studies. In a relatively uniform region, Pn/Lg and Pn/Sn will not depend significantly on event-to-station azimuth. Thus, the simplest corrections are those which depend only on distance. If this function of distance were known, then it would be a simple matter to correct each discriminant so that the corrected training set would contain events which were all samples from the same distribution. Since this function of distance is not known, *a priori*, it must be estimated from the data. It has been suggested (e.g., Sereno, 1990) that a function of the form

$$\mathrm{Pn/Lg}(f) = \beta(f)(\Delta/\Delta_0)^{\alpha(f)}, \tag{1}$$

approximates the distance dependence, where Δ is the epicentral distance. Similar dependence is assumed for Pn/Sn, but with different coefficients. The unknown coefficients, α and β, which depend on the frequency band, f, can be estimated using a least-squares procedure, and the constant Δ_0 is an arbitrary reference distance. If the logarithm is taken of both sides of Eq. (1), the resulting equation is linear in $\log\Delta$. If Eq. (1) is valid, then a data plot of $\log(\mathrm{Pn/Lg})$ versus $\log\Delta$ would approximate a straight line with slope α. Once α has been estimated, the discriminant is corrected using the equation

$$\mathrm{Pn/Lg}(f)_{\mathrm{corrected}} = (\Delta/\Delta_0)^{-\hat{\alpha}(f)}\mathrm{Pn/Lg}(f)_{\mathrm{uncorrected}}, \tag{2}$$

where $\hat{\alpha}$ is the least-squares estimate of α. In Section 4, this formula will be used to compute regional distance corrections at each of the Primary and Auxiliary seismic stations for which there are sufficient data, based on the IMS data sets described in the following section.

3. IMS Regional Seismic Data

At the time of this study, January 1997, there were 35 Primary and 51 Auxiliary seismic stations in the IMS network; these IMS stations are considered in this report. Note, however, that this list changes periodically. The 14 arrays and 21 three-component (3-C) stations of the Primary network are listed in Table 1 and the 4 arrays and 32 three-component (3-C) stations of the Auxiliary network are listed in Table 2. The numbers for the Auxiliary network exclude 15 stations (indicated by a "#"), which are accessed by modem and are not presently used by the IDC, except under special circumstances, and for which there are currently no data available in the PIDC archive database (IDC Performance Report, 28 January 1997).

Figure 1 shows the number of regional events for each Primary station between 10 September 1995 (950910) and 15 January 1997 (970115). A regional event is defined as one within 20 degrees of the station with at least one of the six discriminants (Pn/Lg and Pn/Sn in the 2–4, 4–6, and 6–8 Hz bands) measured with SNR greater than 1.5 (depicted by the hashed bars). Also indicated in the plot by the solid bars are those events with at least one measurement with SNR greater than 2.0. Figure 2 is a similar plot for the Auxiliary stations. In the 16 months represented in these plots it can be seen that the station with the most events, WRA, detects about 30 events per month with SNR > 1.5, while there are some stations with less than one event per month on average. The fraction of events with SNR > 1.5, which also have SNR > 2.0, is about 60%.

Figure 3 shows the locations of all on-line Primary and Auxiliary stations. The stations depicted by green squares have at least 20 regional events with at least one discriminant with SNR > 2.0. Stations depicted by blue triangles have at least 20 regional events with SNR > 1.5 but not 20 or more events with SNR > 2.0. Stations that have less than 20 regional events are depicted by red circles. There are 32 stations that are green and another 19 that are blue, leaving 35 of the 86 stations with less than 20 regional events in this 16-month period (depicted by the red circles).

Figure 4 is a histogram of the number of regional events above mb 3.5 as a function of the number of discriminants measured (there can be one through six discriminants measured). Figure 5 is a similar plot giving the percentage of the total of 2797 regional events in the 16-month period with one through six discriminants measured. As seen in the plots, most events have only one, two or three discriminants measured. Less than 5% of the events have measurements with SNR > 1.5 for all six discriminants, meaning that more than 95% of regional events have some missing data. It is important to systematically determine the physical effects (e.g., blockage, attenuation, etc.) leading to this. This is an involved and complicated issue for future study.

Table 1. Primary seismic stations.

Code	Latitude	Longitude	Station Name, Location	Type	# of Elements
ABKT	37.9304	58.1189	Alibek, Turkmenistan	3C	
ARCES	69.5349	25.5058	ARCESS Array, Norway	Array	25
ASAR	-23.6664	133.9044	Alice Springs Array, Australia	Array	19
BDFB	-15.6440	-48.0141	Brasilia, Brazil	3C	
BGCA	5.1761	18.4242	Bogoin, Central African Republic	3C	
BJT	40.0183	116.1679	Baijiatuan, China	3C	
BOSA	-28.6137	25.2559	Boshof, South Africa	3C	
CMAR	18.4575	98.9429	Chiang Mai Array, Thailand	Array	18
CPUP	-26.3306	-57.3292	Villa Florida, Paraguay	3C	
DBIC	6.6701	-4.8563	Dimbroko, Ivory Coast	3C	
ESDC	39.6755	-3.9617	Sonseca Array, Spain	Array	19
FINES	61.4436	26.0771	FINESS Array, Finland	Array	16
GERES	48.8451	13.7016	GERESS Array, Germany	Array	25
HIA	49.2667	119.7417	Hailar, China	3C	
ILAR	64.7714	-146.8866	Eielson Array, Alaska	Array	21
KBZ	43.7286	42.8975	Khabaz, Russia	3C	
KSAR	37.4421	127.8844	Wonju Array, South Korea	Array	25
LOR	47.2683	3.8589	Lormes, France	3C	
LPAZ	-16.2879	-68.1307	La Paz, Bolivia	3C	
MAW	-67.6039	62.8706	Mawson, Antarctica	3C	
MJAR	36.5427	138.2070	Matsushiro Array, Japan	Array	7
MNV	38.4328	-118.1531	Mina, Nevada	3C	
NORES	60.7353	11.5414	NORESS Array, Norway	Array	25
NRI	69.0061	87.9964	Norilsk, Russia	3C	
PDAR	42.7667	-109.5579	Pinedale Array, Wyoming	Array	13
PDY	59.6333	112.7003	Peleduy, Russia	3C	
PLCA	-40.7306	-70.5500	Paso Flores, Argentina	3C	
SCHQ	54.8319	-66.8336	Schefferville, Canada	3C	
STKA	-31.8769	141.5952	Stephens Creek, Australia	3C	
TXAR	29.3338	-103.6670	TXAR Array, Texas	Array	9
ULM	50.2486	-95.8755	Lac du Bonnet, Canada	3C	
VNDA	-77.5139	161.8456	Vanda, Antarctica	3C	
WRA	-19.9426	134.3394	Warramunga Array, Australia	Array	20
YKA	62.4932	-114.6053	Yellowknife Array, Canada	Array	22
ZAL	53.6167	84.7917	Zalesovo, Russia	3C	

Table 2. Auxiliary seismic stations.

Code	Latitude	Longitude	Station Name, Location	Type	# of Elements
AAE #	9.0292	38.7656	Addis Ababa, Ethiopia	3C	
AFI #	-13.9093	-171.7773	Afiamalu, Western Samoa	3C	
ALQ	34.9425	-106.4575	Albuquerque, New Mexico	3C	
AQU #	42.3540	13.4050	L'Aquila, Italy	3C	
ARU	56.4302	58.5625	Arti, Russia	3C	
BBB	52.1847	-128.1133	Bella Bella, Canada	3C	
BORG	64.7474	-21.3268	Borgarfjordur, Iceland	3C	
CTA	-20.0885	146.2540	Charters Towers, Australia	3C	
DAV #	7.0878	125.5747	Davao, Philippines	3C	
DAVOS	46.8394	9.7943	Davos, Switzerland	3C	
DLBC	58.4372	-130.0272	Dease Lake, Canada	3C	
EKA	55.3332	-3.1588	Eskdalemuir Array, Scotland	Array	20
ELK	40.7448	-115.2388	Elko, Nevada	3C	
FITZ	-18.1030	125.6430	Fitzroy Crossing, Australia	3C	
FRB	63.7467	-68.5467	Iqaluit, Canada	3C	
HFS	60.1344	13.6968	Hagfors Array, Sweden	Array	8
HNR #	-9.4322	159.9471	Honiara, Solomon Islands	3C	
INK	68.3067	-133.5200	Inuvik, Canada	3C	
ISG	24.3800	124.2300	Ishigaki-jima, Japan	3C	
JER	31.7719	35.1972	Jerusalem, Israel	3C	
JTS	10.2908	-84.9525	Las Juntas de Abangares, Costa Rica	3C	
KIEV #	50.6944	29.2083	Kiev, Ukraine	3C	
KKJ	41.7800	140.1800	Kaminokuni, Japan	3C	
KVAR	43.9557	42.6952	Kislovodsk Array, Russia	Array	4
LSZ #	-15.2766	28.1882	Lusaka, Zambia	3C	
MBC	76.2420	-119.3600	Mould Bay, Canada	3C	
MLR	45.4917	25.9437	Muntele Rosu, Romania	3C	
MSEY	-4.6737	55.4792	Mahe, Seychelles	3C	
NEW	48.2633	-117.1200	Newport, Washington	3C	
NIL	33.6500	73.2512	Nilore, Pakistan	3C	
NNA	-11.9875	-76.8422	Nana, Peru	3C	
NWAO #	-32.9266	117.2333	Narrogin, Australia	3C	
OBN	55.1167	36.6000	Obninsk, Russia	3C	
OGS	27.0500	142.2000	Ogasawara, Japan	3C	
PFO	33.6092	-116.4550	Pinon Flat, California	3C	
PMG #	-9.4092	147.1539	Port Moresby, New Guinea	3C	
PTGA #	-0.7308	-59.9666	Pitinga, Brazil	3C	
RAR #	-21.2125	-159.7733	Rarotonga, Cook Islands	3C	
RPN	-27.1267	-109.3344	Rapanui, Easter Island	3C	
SADO	44.7694	-79.1417	Sadowa, Canada	3C	
SDV #	8.8790	-70.6330	Santo Domingo, Venezuela	3C	
SFJ #	66.9967	-50.6152	Sondre Stromfjord, Greenland	3C	
SHK	34.5300	132.6800	Shiraki, Japan	3C	
SNZO #	-41.3103	174.7046	South Karori, New Zealand	3C	
SPITS	78.1777	16.3700	Spitsbergen Array, Norway	Array	9
SUR	-32.3797	20.8117	Sutherland, South Africa	3C	
TKL	35.6580	-83.7740	Tuckaleechee Caverns, Tennessee	3C	
TSK	36.2108	140.1097	Tsukuba, Japan	3C	
TSUM #	-19.2022	17.5838	Tsumeb, Namibia	3C	
ULN	47.8652	107.0528	Ulaanbaatar, Mongolia	3C	
VRAC	49.3083	16.5935	Vranov, Czech Republic	3C	

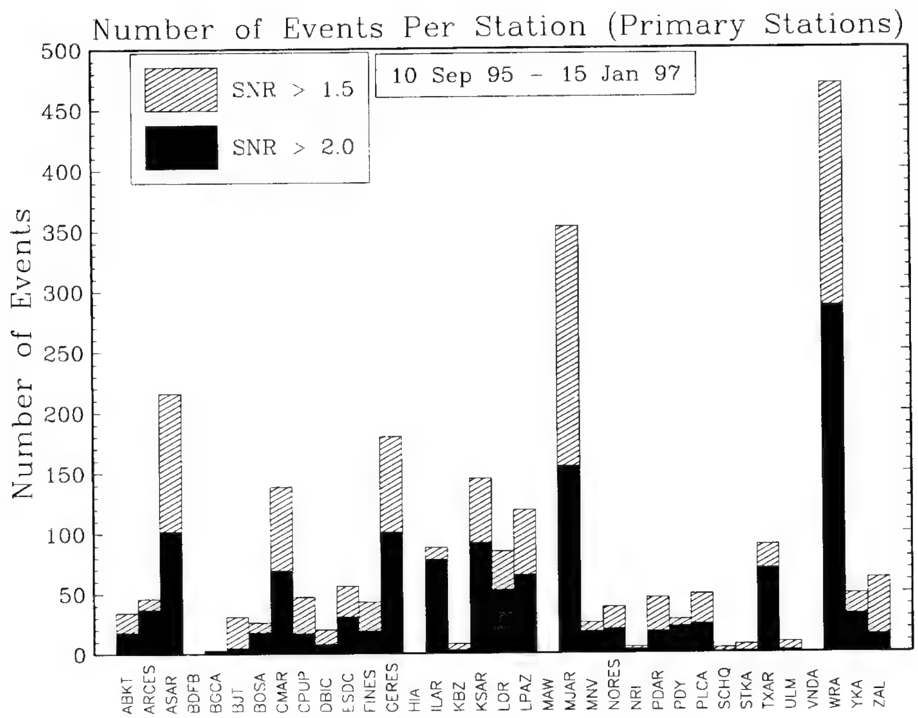

Figure 1. **Number of regional events above mb 3.5 per Primary station between 950910 and 970115.**

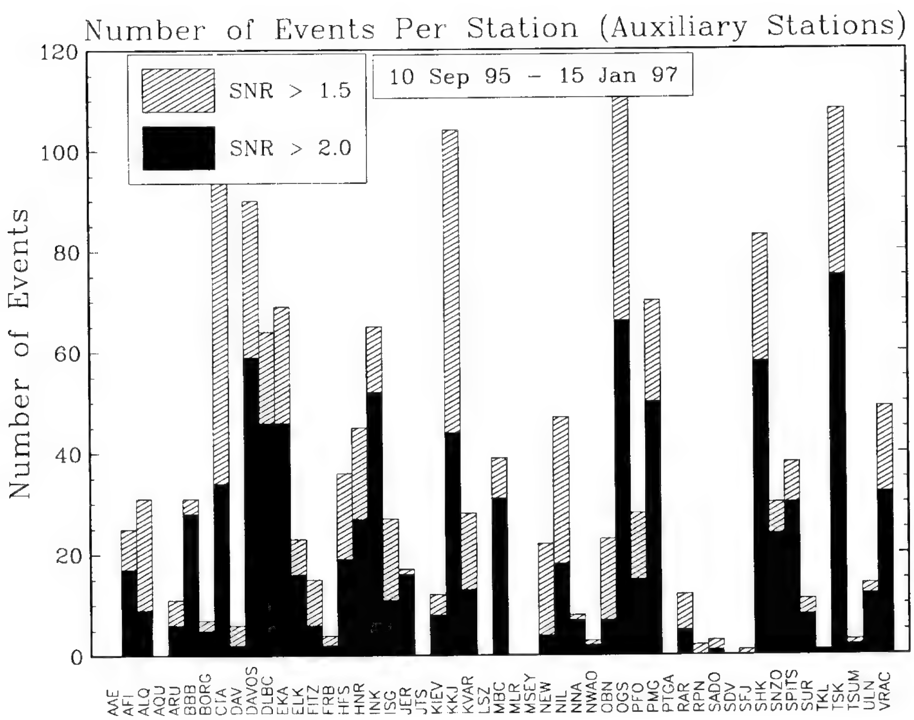

Figure 2. **Number of regional events above mb 3.5 per Auxiliary station between 950910 and 970115.**

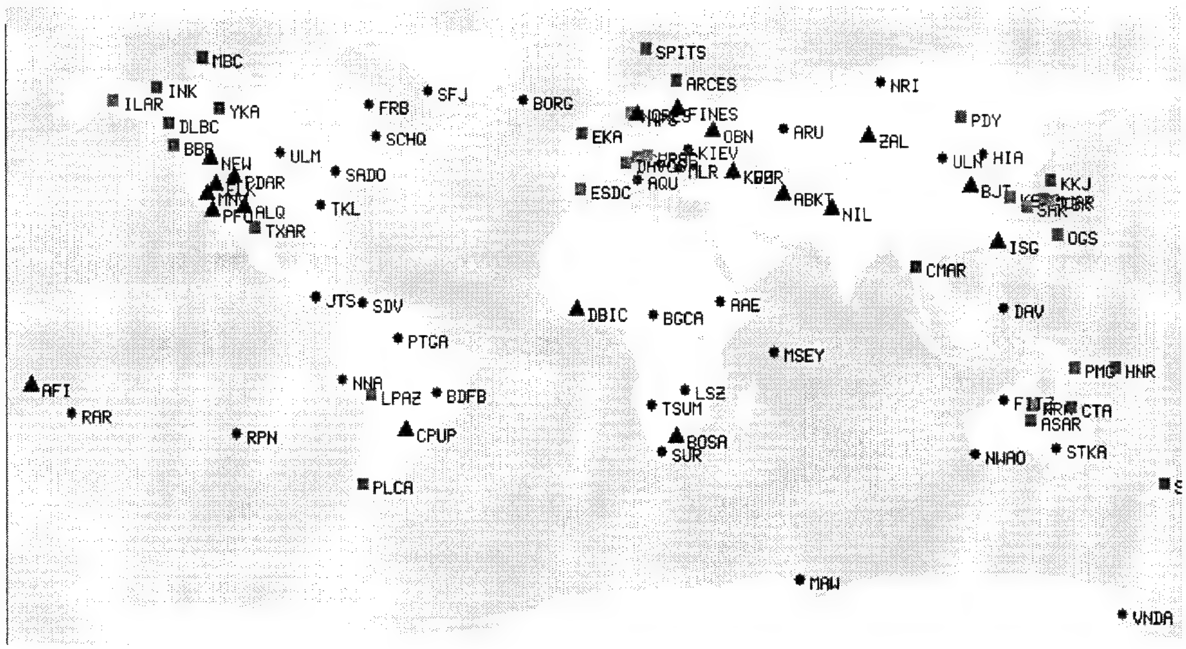

Figure 3. **Locations of Primary and Auxiliary stations. Green squares: at least 20 regional events with at least one discriminant with SNR > 2.0; Blue triangles: at least 20 regional events with at least one discriminant with SNR > 1.5; Red circles: less than 20 regional events.**

Often an event produces regional measurements at more than one station and there has been an event with regional measurements taken by as many as ten stations. Figure 6 plots the distribution of events as a function of the number of stations with at least one discriminant measured with SNR > 1.5. Also plotted is the distribution where at least one discriminant measured with SNR > 2.0. Recall that a regional event is defined to be within 20 degrees (2220 km) of the station. As can be seen in Figure 6, about 67% of the regional events are observed by only one station. Therefore, about one-third of the regional events are observed by more than one station, with about 20% observed at two stations. (Note: by observed we mean there is at least one discriminant with SNR > 1.5 that can be measured, which requires Pn in one of the 2–4 Hz, 4–6 Hz, or 6–8 Hz frequency bands with SNR > 1.5 and either Lg or Sn in the same frequency band with SNR > 1.5).

Figures 7 and 8 plot the distributions of events as a function of the number of stations, but for each of the six discriminants individually. Figure 7 includes each of the six discriminants on the same plot, whereas Figure 8 has six separate plots, one for each discriminant. These plots show that each of the six discriminants are measured with approximately the same frequency, on average. There is no one discriminant that is measured much more often, on average, than the others.

In the remainder of the report we describe how these data are distance-corrected and how we categorize each station in terms of the utility of their training sets and distance corrections.

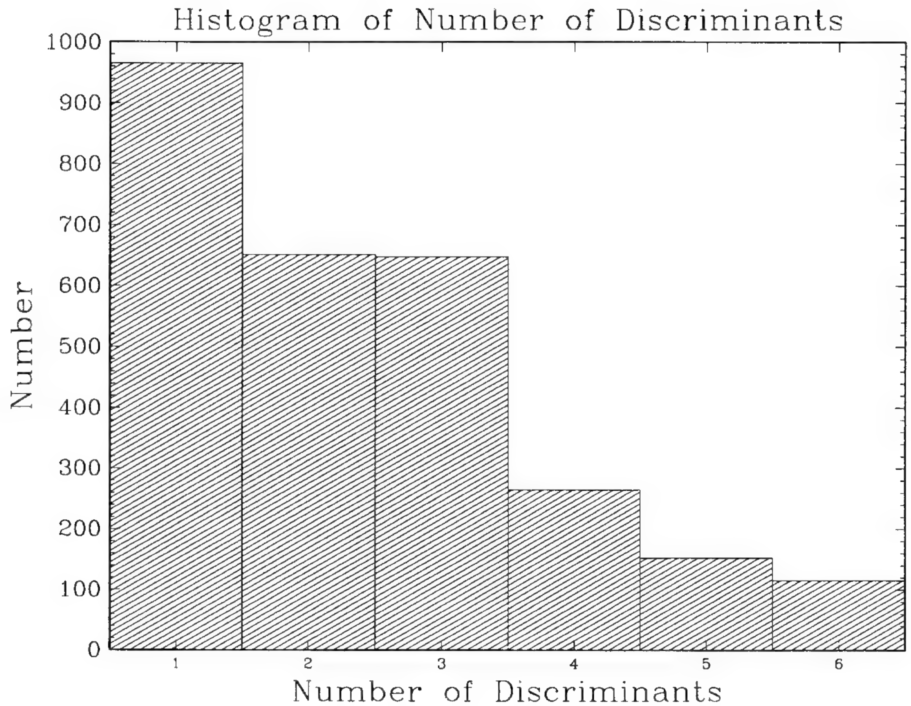

Figure 4. Number of regional events with one through six discriminants measured.

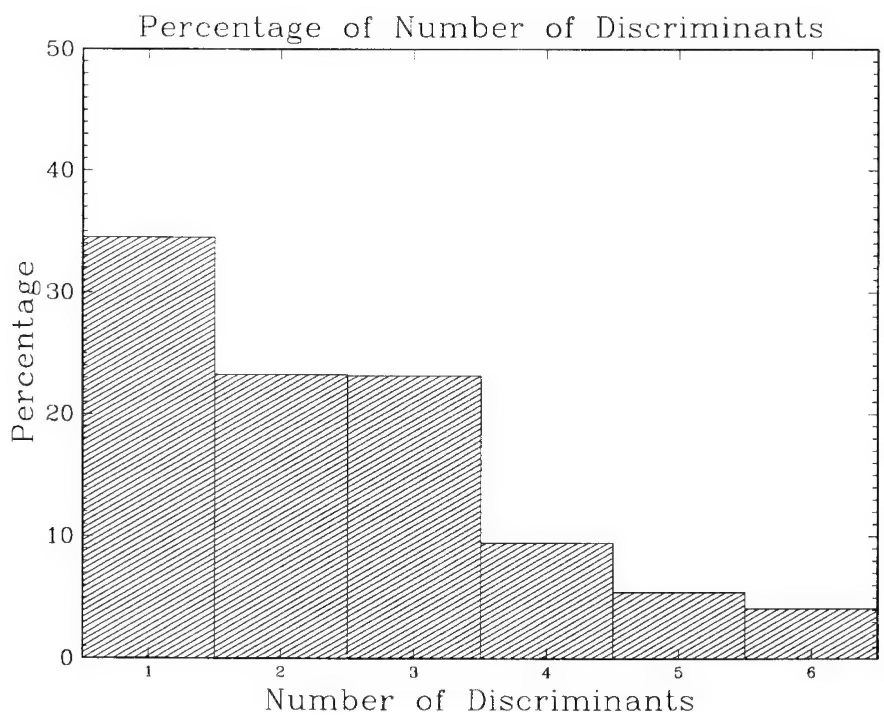

Figure 5. Percentage of regional events with one through six discriminants measured.

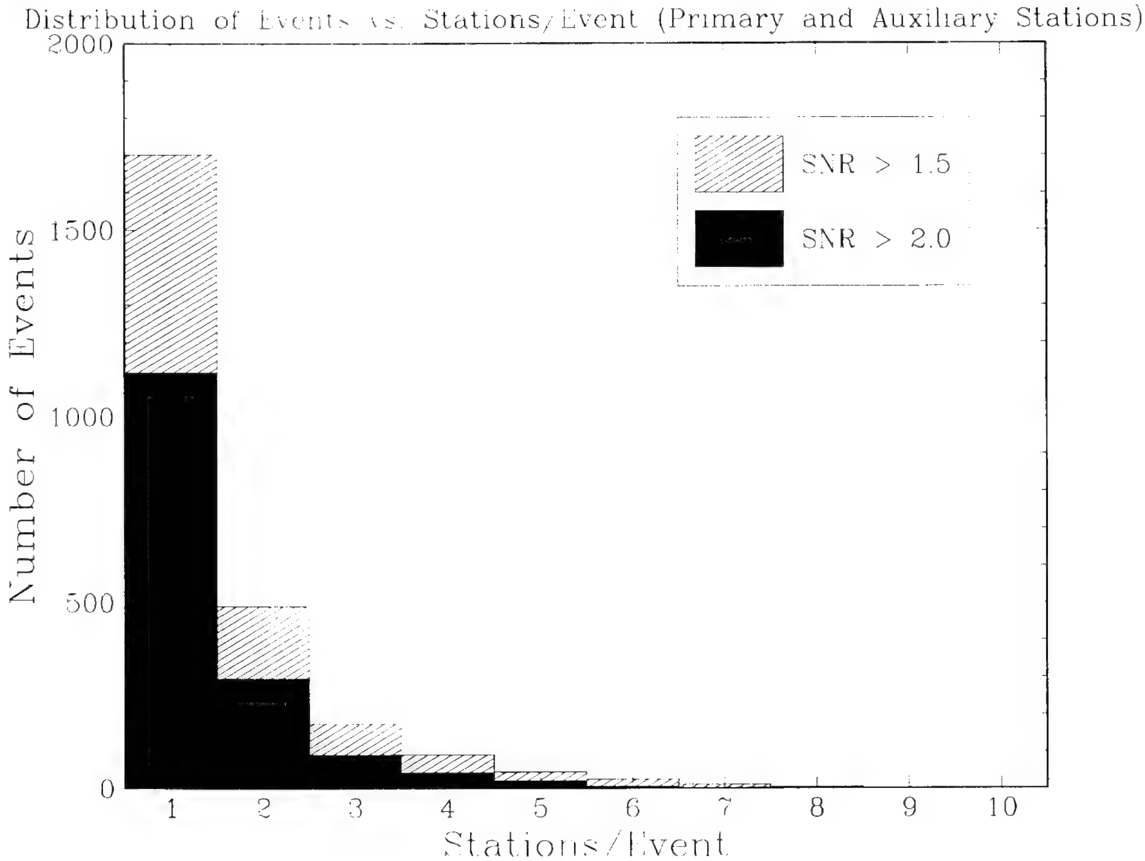

Figure 6. **Distribution of regional events as a function of the number of observing stations per event for Primary and Auxiliary stations combined.**

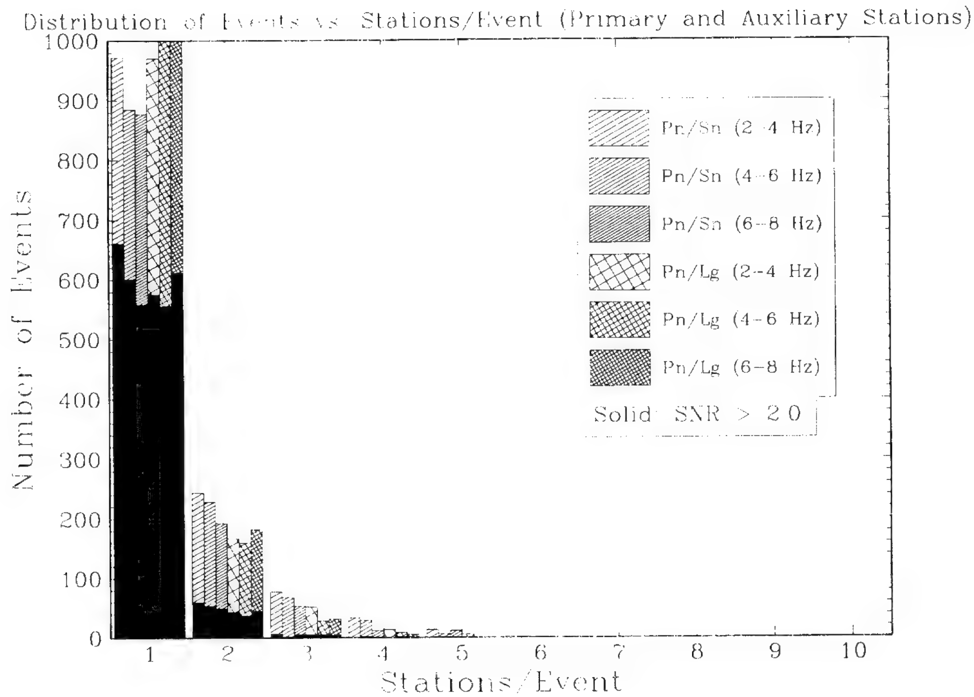

Figure 7. **Distribution of regional events by individual discriminant (combined).**

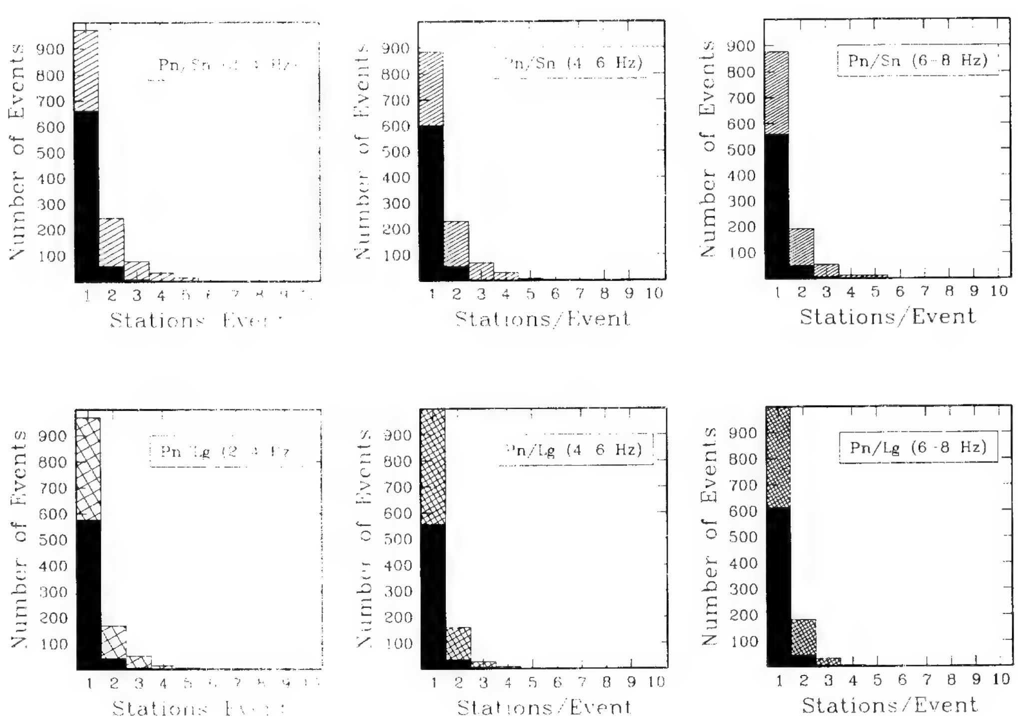

Figure 8. **Distribution of regional events by individual discriminant (separate).**

4. Distance Corrections

As described in Section 2, a training set is most useful when it is composed of events all from the same distribution. In this case a test event is either in a low probability region of the test space and is considered an outlier, e.g., it belongs to another population (such as explosions), or it is in a high probability region and is consider a sample from the training set population (earthquakes).

Previous studies have provided convincing evidence that if events at substantially different distances are to be combined into the same training set, distance corrections are essential. At station WMQ in China, Fisk et al. (1996b) found that distance dependencies are large enough to shift the mean of the regional discriminants for the earthquake population at one distance to the mean of the explosion population at another distance. Similar phenomena have also been discussed by Fisk et al. (1994, 1995) for events detected at ARCES.

Further, all the experience of which we are aware suggests that the slope, $\alpha(f)$, in Eq. (1), will typically be positive (e.g., Baumgardt and Der, 1994; Fisk et al., 1995, 1996b; Sereno, 1990). As we shall describe in detail below, a straightforward fitting procedure sometimes produces negative or unusually large positive values when applied to the IMS data used in this study. We are not confident in the validity of some of the results we have obtained. Below we propose an interim procedure which we apply to the IMS data here, but we shall continue studies either to validate the procedure or, as we believe may be necessary, propose a modified procedure.

It is possible that the negative values of $\alpha(f)$ we have obtained are correct; we know of no theory which precludes that possibility. It is perhaps more likely that our results are due to mixing events which cannot be mapped onto a single distribution by a relation of the form given by Eq. (1). That would be the case, for example, if there is a pronounced azimuth dependence to the distribution functions for the regional discriminants. In that case, the data samples we use for the fit are really drawn from a mixture of distributions and fitting the results to Eq. (1) could produce results of the type we have observed even if, along any given azimuth, Eq. (1) is a very good approximation with a positive value of $\alpha(f)$, but with different parameter values for different azimuths. Similar considerations would apply if the propagation characteristics change when the signal passes from one tectonic subregion to another along the same azimuth.

As data from the IMS network have accumulated and we have come to better understand some aspects of the data structures that the system will have to analyze, we have become more interested in the possibility of choosing subsets of events seen at a given station to form training sets more appropriate for testing a given new event, than using the entire set of regional events

seen at that station would be. One possible procedure of this type would be to form a training set from events whose distance from the station is not very different from that of the event to be tested. Some of the results we shall present on attempting to fit distance corrections point out the desirability of such a procedure if one can be developed. We present some preliminary results from these studies below. It seems likely that many, perhaps a large majority of events, can be tested using localized training sets for which distance dependence plays an insignificant role.

In Figure 9, plots are shown for each discriminant (Pn/Lg and Pn/Sn in the 2–4, 4–6, and 6–8 Hz bands) of the log (base 10) of the discriminant value versus the log (base 10) of the distance (in km) from station CMAR for each event in the raw training set. In the plots, the size of the cross-shaped marker is proportional to the SNR of that measurement. All events in the set have magnitude mb > 3.5 to prevent potential contamination from mining blasts.

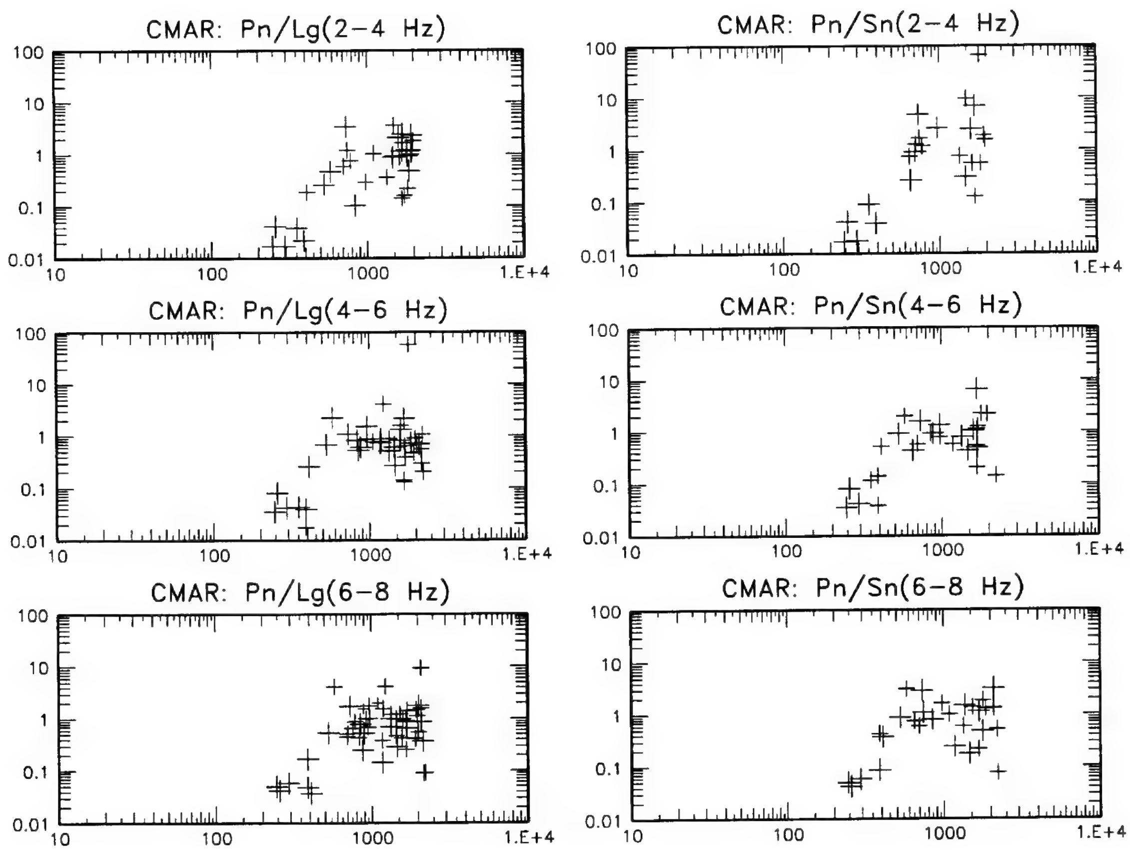

Figure 9. **Log-log scatterplots of discriminant versus distance for station CMAR.**

In general, smaller values of each discriminant are associated with smaller distances from the station. It is clear that for a fixed distance from the station there is considerable spread in the values. On average, however, it is apparent that the mean of the values at a fixed distance is an increasing function of distance, since Lg and Sn amplitudes typically attenuate faster with distance than corresponding Pn amplitudes. If the relationships of log Pn/Sn or log Pn/Lg with log distance is approximately linear, then the two parameters describing that straight line can be estimated using standard statistical regression analysis. Statistical analysis can quantify in a certain sense how good a line fits a set of points, but only physical reasoning and visual inspection can determine if the linear fit is actually appropriate. It could be the case that no one function of distance describes the entire set of points. For example, the set of points could be composed of samples from two or more populations of events at various distances, possibly along two different directions for which the relative attenuation of Pn and Lg (and Sn) are different. This would, in principle, yield plots with points that should be separated into two or more sets, with a possibly different function describing the means as functions of distance. In our case we will determine whether a straight line fit is a good assumption by examining the scatterplots for each station.

For each of the Pn/Lg plots in Figure 9 in the three frequency bands, 2–4, 4–6, and 6–8 Hz, we now fit a straight line of the form

$$\log(\mathrm{Pn}/\mathrm{Lg}(f)) = \alpha(f)\log(\Delta/\Delta_0) + \log(\beta(f)), \tag{3}$$

which is the logarithm of Eq. (1). We also fit the three Pn/Sn plots with a similar equation. Here, Δ is the epicentral distance and the constant Δ_0 is a reference distance, relative to which the discriminant values are corrected. We arbitrarily set Δ_0 at 1500 km, roughly the mean epicentral distance of the 2797 regional events considered in this study. The unknown coefficients, $\alpha(f)$ and $\beta(f)$, are estimated for each frequency band using weighted least squares, where the weights are chosen to be proportional to the signal-to-noise ratio. Thus, events with high SNR have more influence on the linear fits than ones with poor SNR.

Figure 10 shows the same scatterplots as Figure 9 with the lines of best-fit superimposed. The estimated slopes of each of these lines are significant at the 0.01 level, using a test based on Student's t-statistic, which assumes that the errors are normally distributed. In other words, if the true slope were actually zero, and if the errors are normally distributed, then only 1% of the time would an estimated slope be randomly greater than a threshold based on the t-distribution. The data can now be corrected by applying $\mathrm{Pn}/\mathrm{Lg}(f)_{\mathrm{corrected}} = (\Delta/\Delta_0)^{-\hat{\alpha}(f)}\mathrm{Pn}/\mathrm{Lg}(f)_{\mathrm{uncorrected}}$ to the discriminant values, where $\hat{\alpha}(f)$ is the estimate of $\alpha(f)$. The intercept, $\beta(f)$, is a constant for each discriminant, which does not have an effect on discrimination.

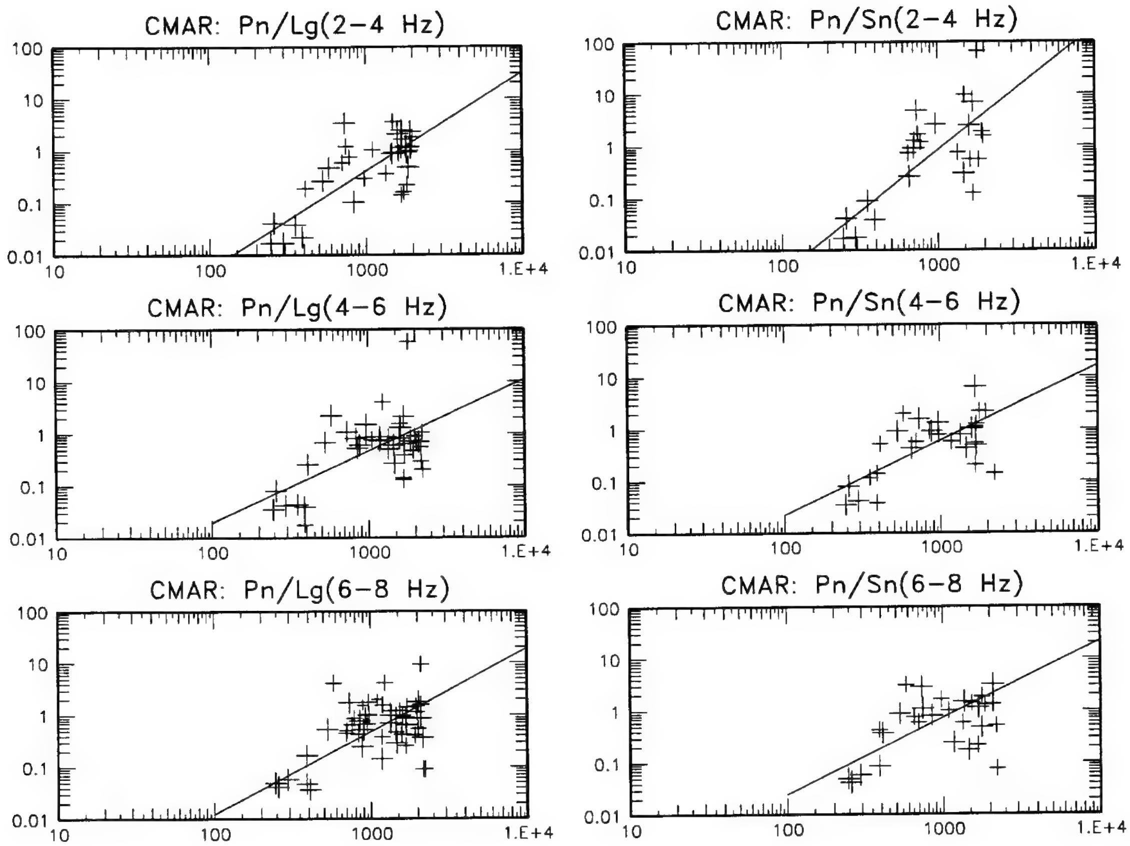

Figure 10. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station CMAR.

Each slope in Figure 10 is a positive number between approximately 1 and 2. This corresponds to a power-law relationship between distance and Pn/Lg or Pn/Sn that falls between linear and quadratic (see Eq. (1)). The positive slope indicates that Lg and Sn are falling off with a higher power of distance than Pn.

When all six discriminants have this expected behavior, positive slopes not greater than 3 for all six discriminants, and there are more than 20 events in the training set, we will refer to such a station as belonging to Category 1. (This and other categories will be defined more precisely in Section 6.) There are a number of stations in the IMS network which have the property that all six discriminants have positive slopes less than 3, including nine Primary stations: CMAR, CPUP, ESDC, GERES, ILAR, KSAR, MJAR, NORES and PDY. Plots for GERES, KSAR, MJAR and NORES are shown in Figures 11–14, respectively.

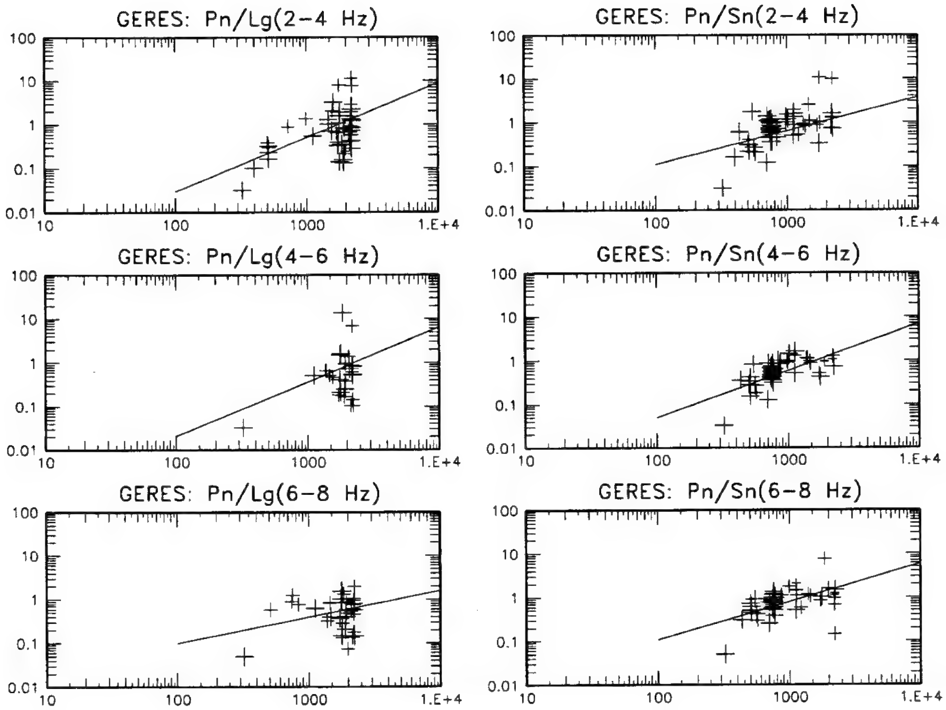

Figure 11. **Log-log scatterplots of discriminant vs. distance with lines of best-fit for station GERES.**

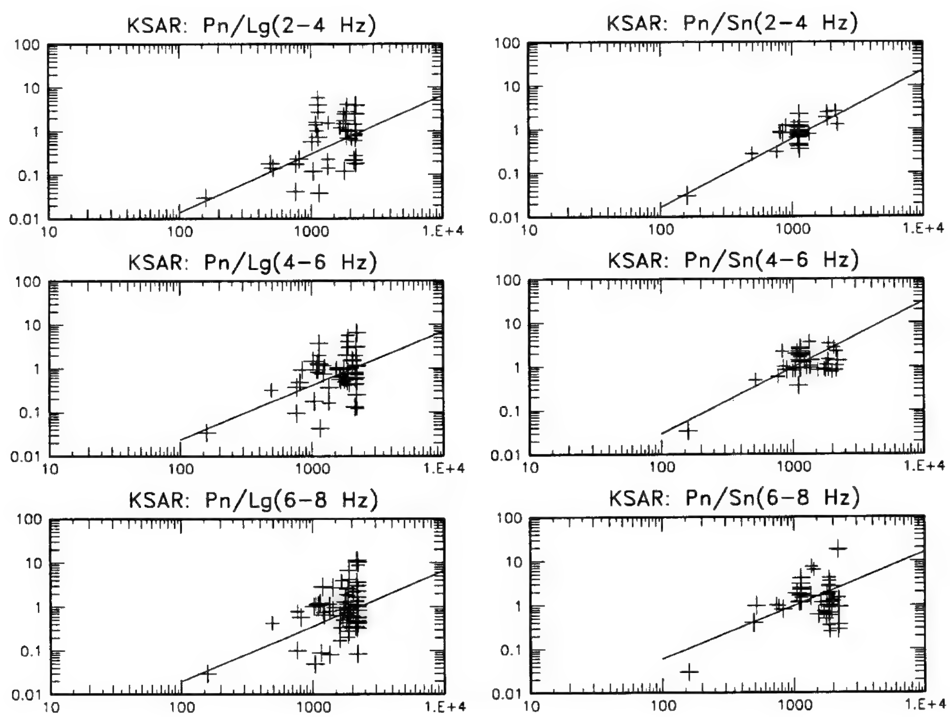

Figure 12. **Log-log scatterplots of discriminant vs. distance with lines of best-fit for station KSAR.**

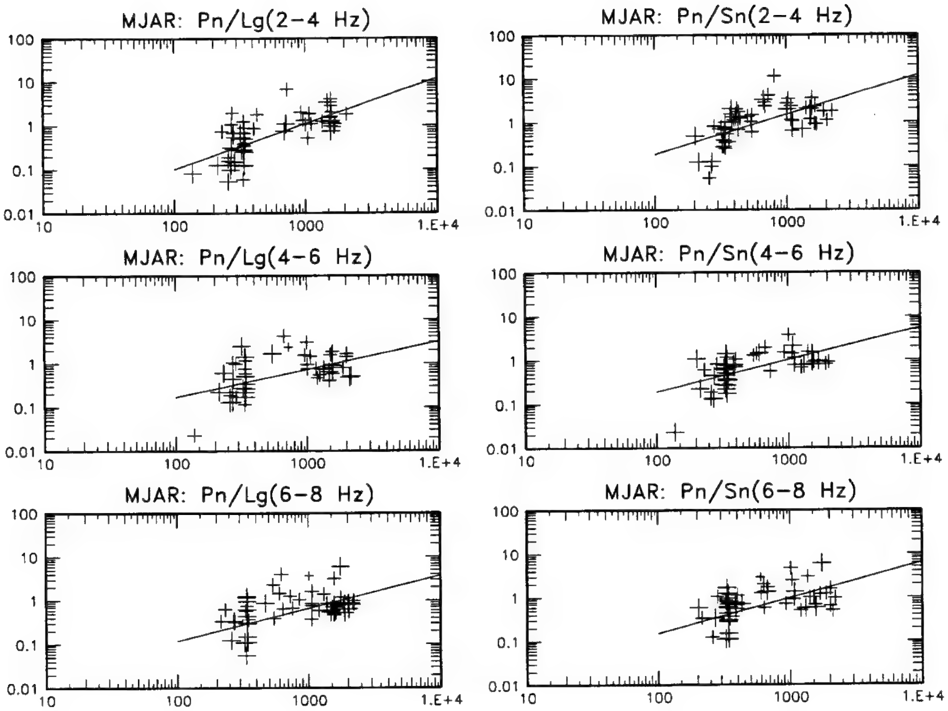

Figure 13. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station MJAR.

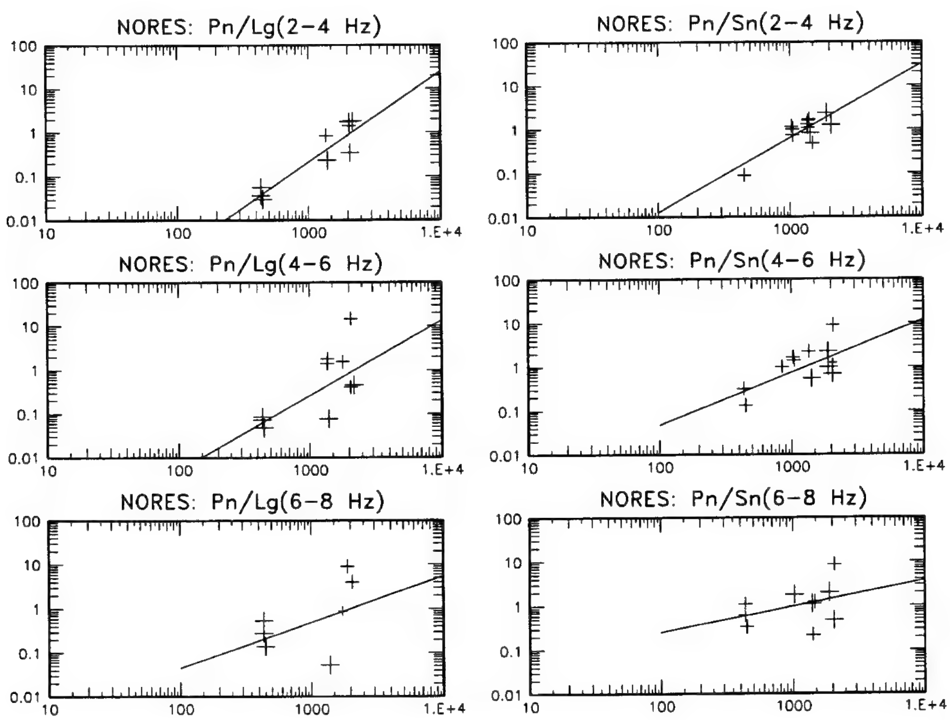

Figure 14. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station NORES.

There are, however, many stations, even those with sufficient data, which have unexpected (or anomalous) slopes, mostly because one or more of the discriminant versus distance plots yield negative slopes. One such Primary station is TXAR. Discriminant versus distance plots for TXAR are shown in Figure 15. In this case, the slopes for Pn/Sn (2–4 Hz) and Pn/Sn (4-6 Hz) are slightly negative, although there are too few data points available for these discriminants, and over too limited a distance range, to reliably estimate these slopes. Additional data must be collected for TXAR and other stations with similar data limitations, before reliable distance corrections can be estimated and utilized.

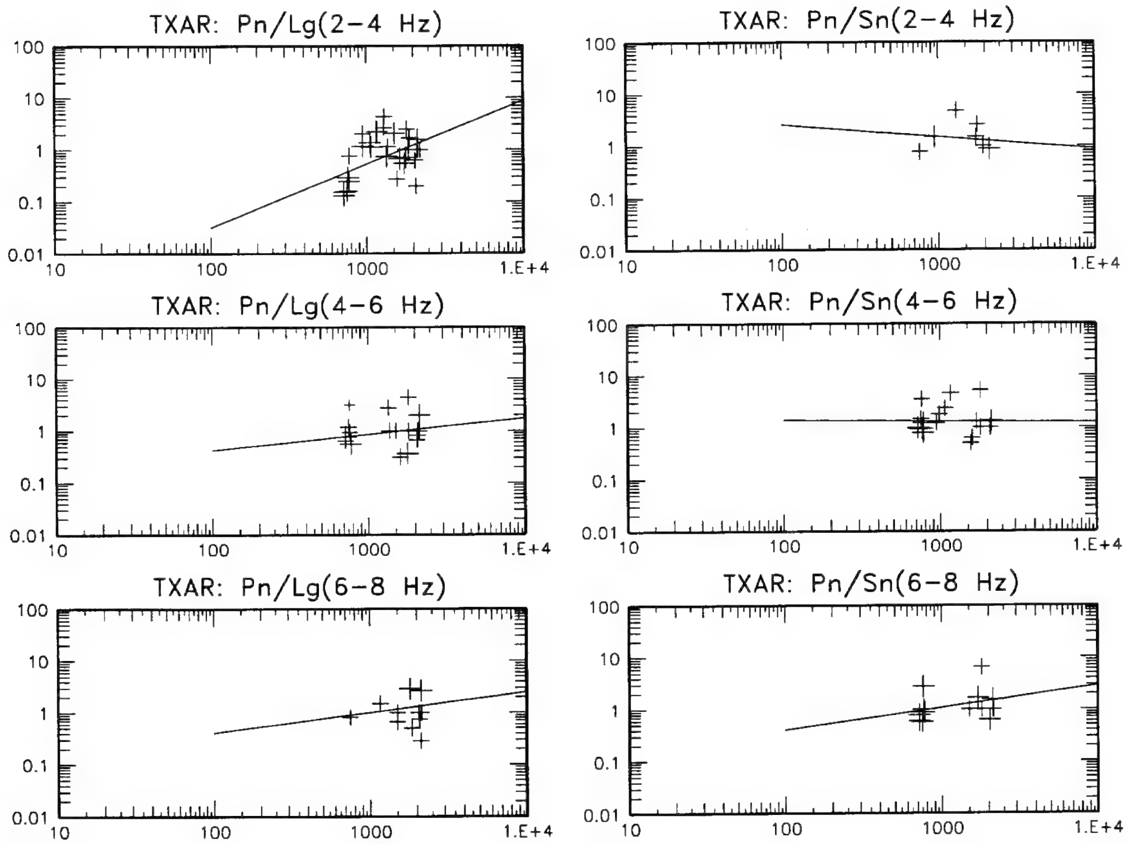

Figure 15. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station TXAR.

A more convincing example of a station with negative slopes for discriminant versus distance plots is LPAZ (Figure 16). Pn/Lg and Pn/Sn in the 4–6 Hz and 6–8 Hz bands all have negative slopes, with the estimated slope for Pn/Lg (4–6 Hz) significant, using the t-statistic test, at 0.01 significance level. Clearly more data and investigation of subregional variations are needed.

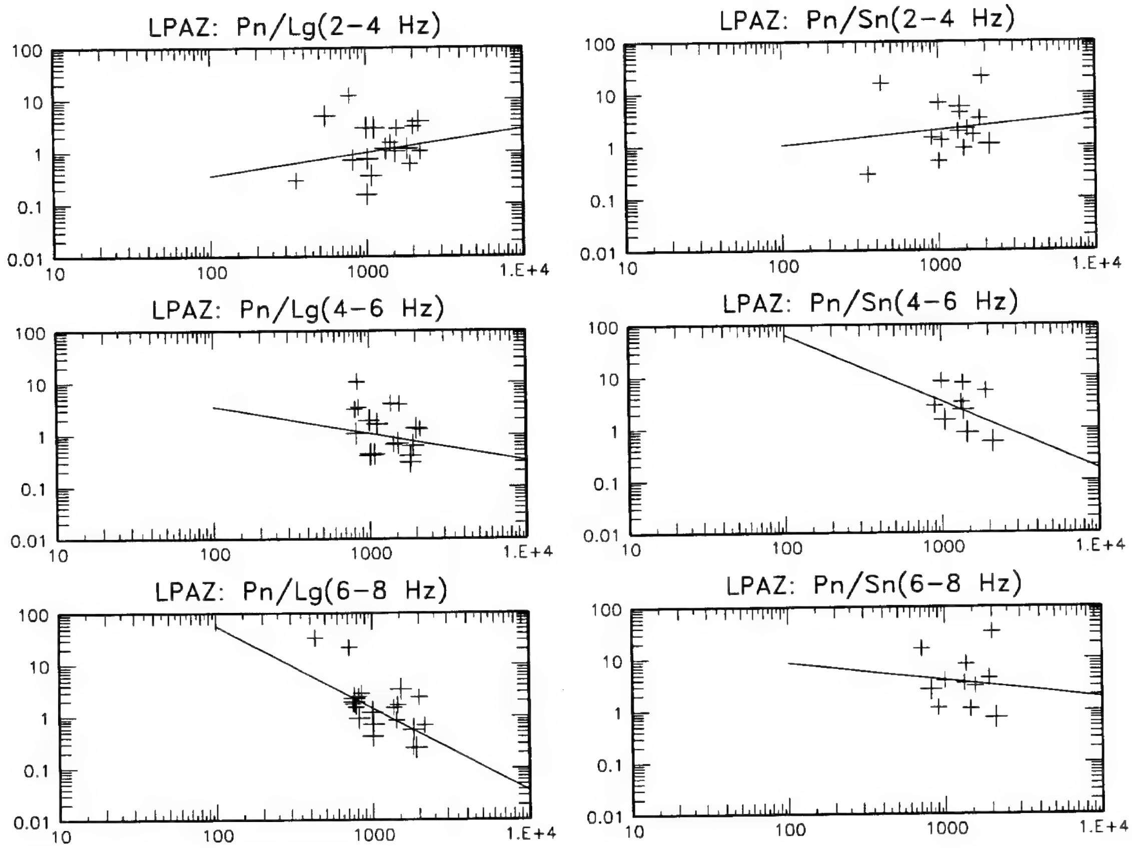

Figure 16. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station LPAZ.

Another set of stations which cannot be categorized as Category 1 (cf. Section 6) are those stations located in Australia, ASAR and WRA. As plotted in Figures 17 and 18, both stations show a number of discriminants with highly significant slopes greater than three. An important feature to notice about both of these stations, however, is that all of the regional events above mb 3.5 fall within a relatively narrow distance range from the station. The reason for this is that almost all of the events above mb 3.5 that are observed at the Australian stations occur in the tectonically-active region near Indonesia. Since any test event above mb 3.5 observed at these stations will almost certainly come from this same active region, it is likely that distance corrections will not be needed, because the test event will be at roughly the same distance as all of the events in the training set. Stations which have this feature are more likely to have suspicious distance corrections than stations having events with a wide spread in regional distances, but effective application of the outlier analysis can usually still be made. Stations such as ASAR and WRA will be termed Category 2, to be defined more precisely below.

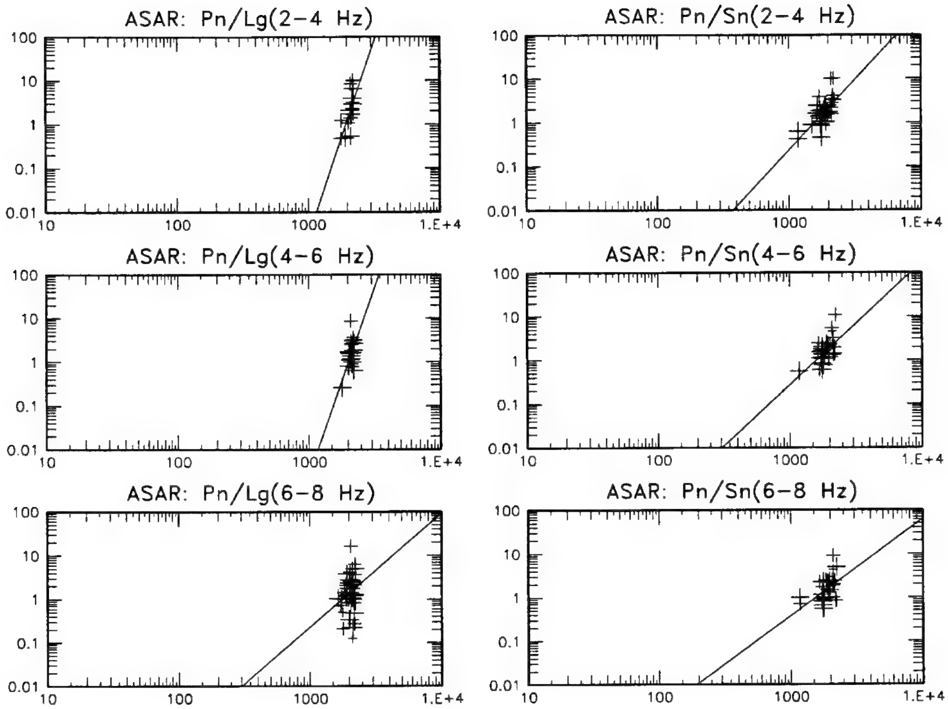

Figure 17. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station ASAR.

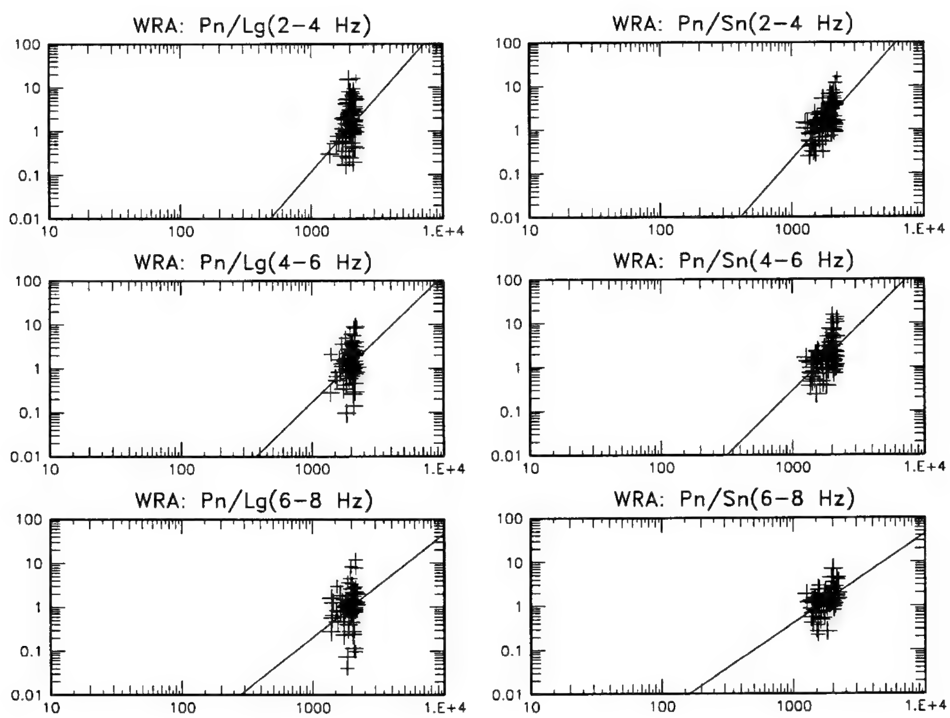

Figure 18. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station WRA.

Finally, we examine stations that, while some of the discriminant versus distances plots have negative slopes, if events with mb < 3.5 are included, the slopes become positive. Examples of such stations are ARCES, LOR and FINES. Notice in Figure 19 that each of the three Pn/Lg discriminants for the training set at ARCES have negative slopes. Figure 20 plots the same six discriminants for all events observed over the same time period at ARCES, including those with mb < 3.5 and no mb measurements. It is clear that there are many more events at ARCES with mb < 3.5 or no mb than events above mb 3.5. Although there is no way to tell from magnitude alone how many of the events below mb 3.5 are mining blasts, it may be the case that most of them are mining blasts. Nevertheless, as can be seen in Figure 20, all of the estimated slopes are now positive. Without further in-depth study, it is not known whether Figure 20 contains mostly mining blasts with a sufficiently different character than the earthquakes in Figure 19 to produce the positive slopes. It is also not clear if the change in slope is due to simply having many more data samples. Figures 21 and 22 show a similar change in slopes for station LOR.

Although the distance corrections which are obtained in Figures 20 and 22 seem to have the expected behavior in their slopes, there is sufficient reason to be suspicious that these are not the true distance corrections for training sets restricted to mb > 3.5. Note that if mining blasts and earthquakes are typically at different distances, inclusion of both can significantly and adversely affect the estimated slopes. These suspicions are great enough to not place stations such as ARCES and LOR in Category 1. Instead they will be put in Category 3, to be defined more precisely below, the category for stations with contradictory slopes.

There are a number of possibilities as to why some regional discriminants have distance dependence of an unexpected character. This problem is not well understood theoretically and there is evidence that the form of dependence assumed here may not always be justified (e.g., Kennett, 1991, 1992). It may be the case that the unusual estimated slopes are accurate, the evidence of which would be strengthened by the future availability of more data. Another possibility is that the discriminant ratios depend on, in addition to distance, other variables, such as direction from the station (i.e., azimuth) and the geophysical properties of the propagation path. Further detailed study of the data is needed to determine if this is the case and what the necessary corrections should be. For now, using only uniform distance corrections, we will consider with suspicion those discriminants with negative or abnormally steep slopes.

Before precisely defining the station categories and assigning each Primary and Auxiliary station to a particular category, we will discuss the distributions of the regional discriminants at each station and outlier removal, whereby anomalous events are removed from the regional data sets and the distance corrections are iteratively re-computed.

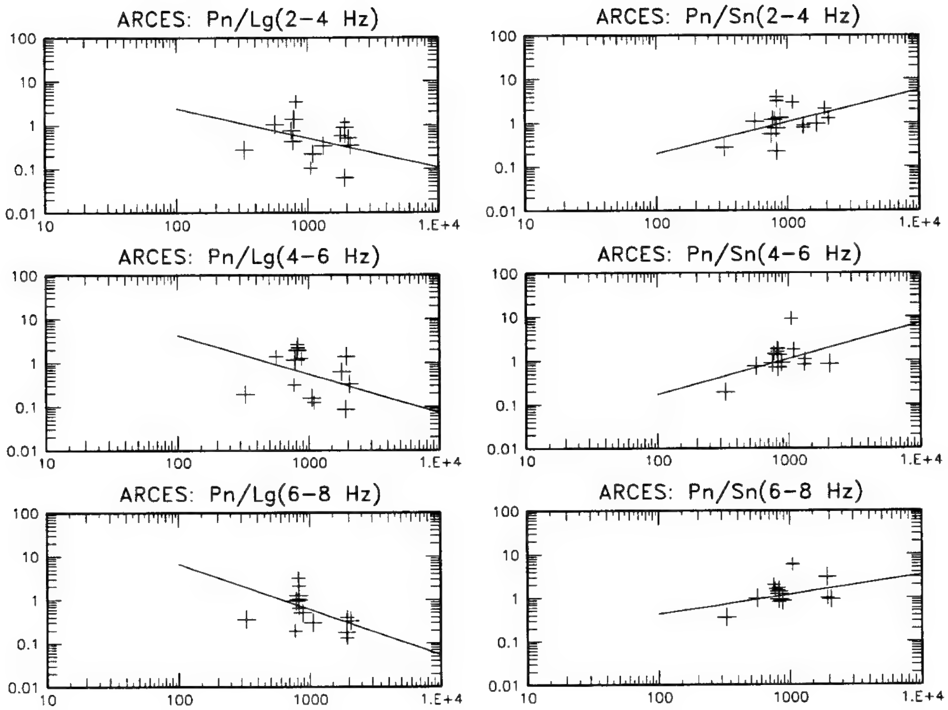

Figure 19. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station ARCES.

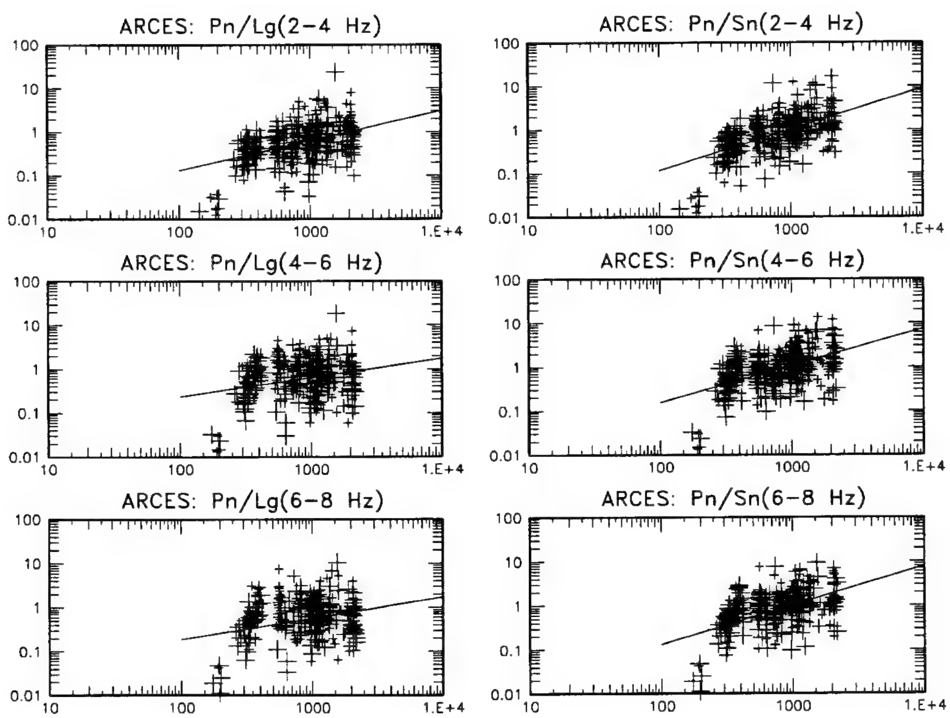

Figure 20. Discriminant vs. distance with lines of best-fit, including events with mb < 3.5, for ARCES.

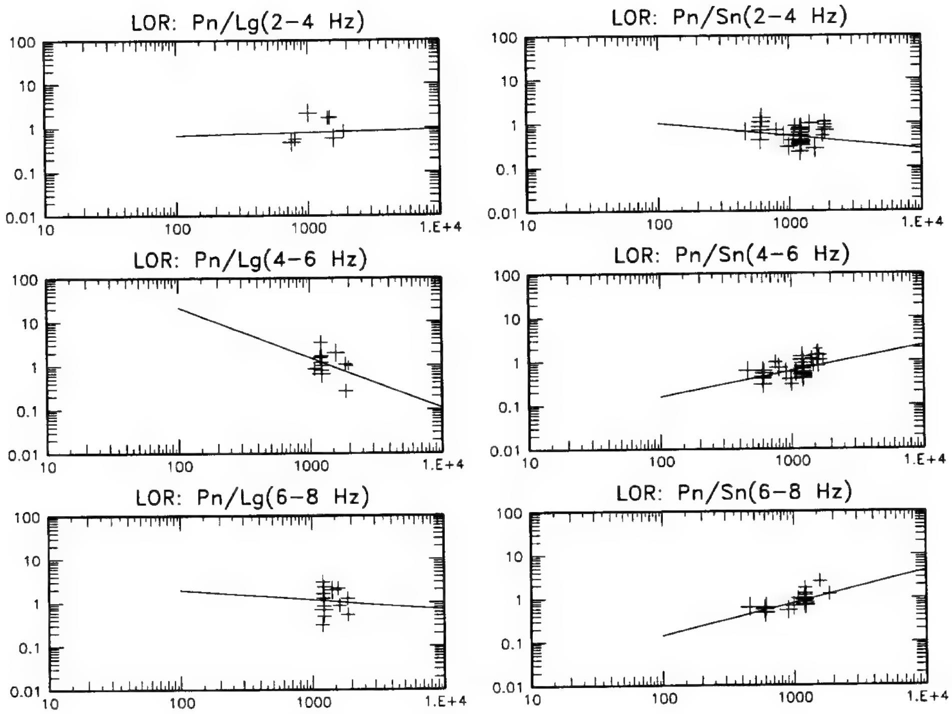

Figure 21. Log-log scatterplots of discriminant vs. distance with lines of best-fit for station LOR.

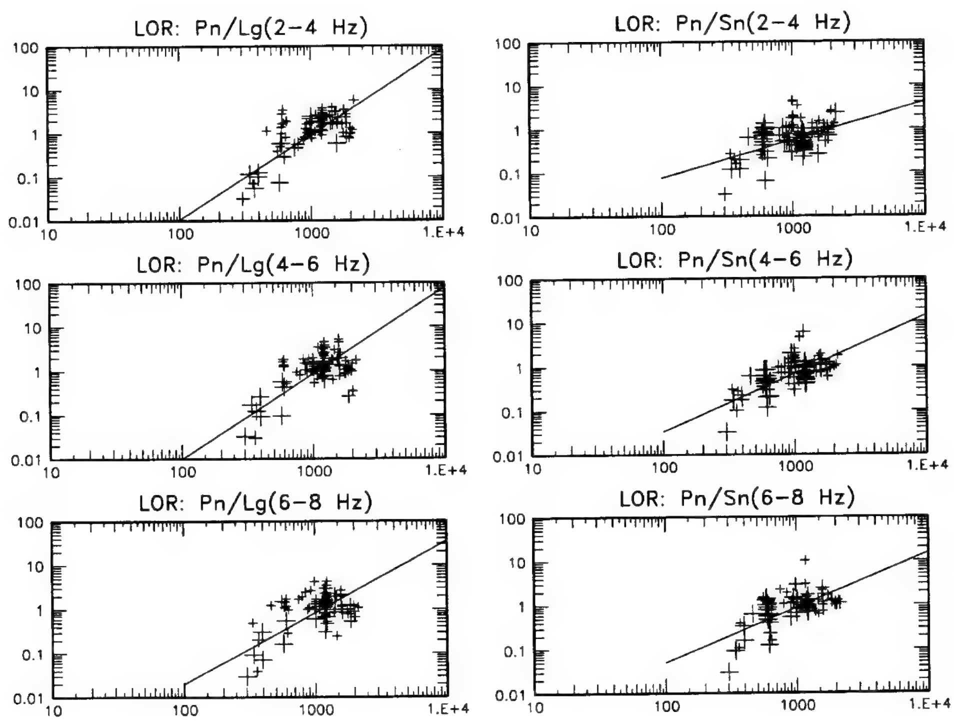

Figure 22. Discriminant vs. distance with lines of best-fit, including events with mb < 3.5, for LOR.

5. Distributions and Outlier Removal

If a suitable set of distance corrections for all six discriminants has been estimated for a training set and applied to all events, then each corrected event in the training set will, in principle, be a sample from the same population. A test event, distance-corrected in the same manner, can then be analyzed with respect to this corrected training set and judged to be an outlier, at a specified significance level, if the value of the generalized likelihood ratio for the test event is less than the threshold value computed from the corrected training set values. The threshold value is typically set so that the probability is 0.01 that the likelihood ratio for the test event is less than the threshold, if it is true that the test event came from the same population as the samples in the training set. For each value of the likelihood ratio, λ, we can define a number, P_λ, referred to as the P-value, such that P_λ is the probability that the likelihood ratio is between 0 and λ (the likelihood ratio must be positive). The threshold value, λ_α, with $\alpha = 0.01$, then has a P-value, $P_{\lambda_\alpha} = \alpha = 0.01$. An outlier would then have a P-value less than $\alpha = 0.01$. In a previous report, Fisk et al. (1995) categorized regional events using the P-value as a scoring metric.

To calculate the generalized likelihood ratio, and, hence, the P-value, for a given test event, it is necessary to know, or to assume, the form of the probability distribution function for the training set (see Fisk et al., 1993). Although not necessary, the calculations become much more tractable if the distributions can be assumed to be normal. In fact, if each discriminant can be assumed to be normally distributed and there are no missing data values, then an analytic calculation of the generalized likelihood ratio can be performed (e.g., Fisk et al., 1996b). If the training sets (after distance correction) are unlikely to be samples from a normal distribution then one of two approaches can be taken: (1) the distribution from which the training samples come can be determined and the appropriate likelihood ratio computed, or, (2) a transformation can be found which transforms the training set to normal and the likelihood ratio computed under the assumption of normality. The first approach is much more difficult to implement than the second, so we will employ the second option.

5.1. Testing for Normality

To test each of the six discriminants for normality we apply three separate tests, the Anderson-Darling (A_n^2) test (Anderson and Darling, 1954), the Wilk-Shapiro (W) test (Shapiro and Wilk, 1965), and Lin and Mudholkar test (Lin and Mudholkar, 1980). If normality is rejected, at the 0.01 significance level, for any of the three tests, then that discriminant is rejected as normal and a transformation is applied. If, after the transformation is applied, the discriminant is still rejected as normal by any of the three tests, then that discriminant is not used in the outlier test.

A class of transformations which has proved useful in transforming univariate data to normal are the Box-Cox transformations (Box and Cox, 1964), of which the logarithm and the square root are special cases. For positive data (any finite set of data, including the discriminants for the test event, can be shifted to all positive values without affecting the outlier test) the Box-Cox transformation is given by

$$x^{(\gamma)} = \frac{x^{\gamma} - 1}{\gamma}. \tag{4}$$

This set of transformations is continuous in the limit $\gamma \rightarrow 0$ and gives $x^{(0)} = \log x$. For each set of discriminant data, γ can be chosen to maximize the likelihood that the transformed set are samples from a normal distribution. An issue with performing the best transformation for each discriminant separately, is that the covariance structure of the original data is transformed in a complicated way. Choosing the same γ to transform each of the six discriminants keeps the covariance structure intact, although some of the discriminants may rejected as normal. We have found that a simpler approach of taking the log of all the data (the same Box-Cox transformation, $\gamma = 0$) transforms nearly all discriminant sets to normal at 0.01 significance level.

Recall that the distance corrections were estimated after taking the logarithm of the data, assuming the distance dependence is linear on the log-log plot, and that the tests of significance of the best-fit lines assumed the errors were normally distributed, after taking the log. Thus, taking the logarithm here provides some consistency in the linked procedures of distance correction and outlier removal (c.f. Section 5.2). Note also that there is no reason to think that the ratio of two positive numbers, such as those for the regional amplitude ratios, should be normally distributed and it is known that the logarithm transformation typically tends to make data more normal.

Figures 23-25 show histograms of the six discriminants for the CMAR training set before and after applying the log transformation. All six sets of discriminants were rejected as normal at the 0.01 significance level before the log transformation was taken, while after the logarithm was applied all six discriminants were accepted as normal. For CMAR, then, it was necessary to transform all the data to be able to apply the outlier test in its normal form. Another way of visualizing the data to check for normality is the quantile-quantile (Q-Q) plot. Figures 26-28 show Q-Q plots for the six discriminants for WRA training set. If a data set is approximately normal, the values of the sample quantiles computed from the data (square markers) should correspond to the quantiles of a normal distribution represented by the straight line. As with CMAR, each of the six discriminant sets for WRA are rejected as normal before the log transformation is made, while all six data sets are accepted as normal, at the 0.01 significance level, after.

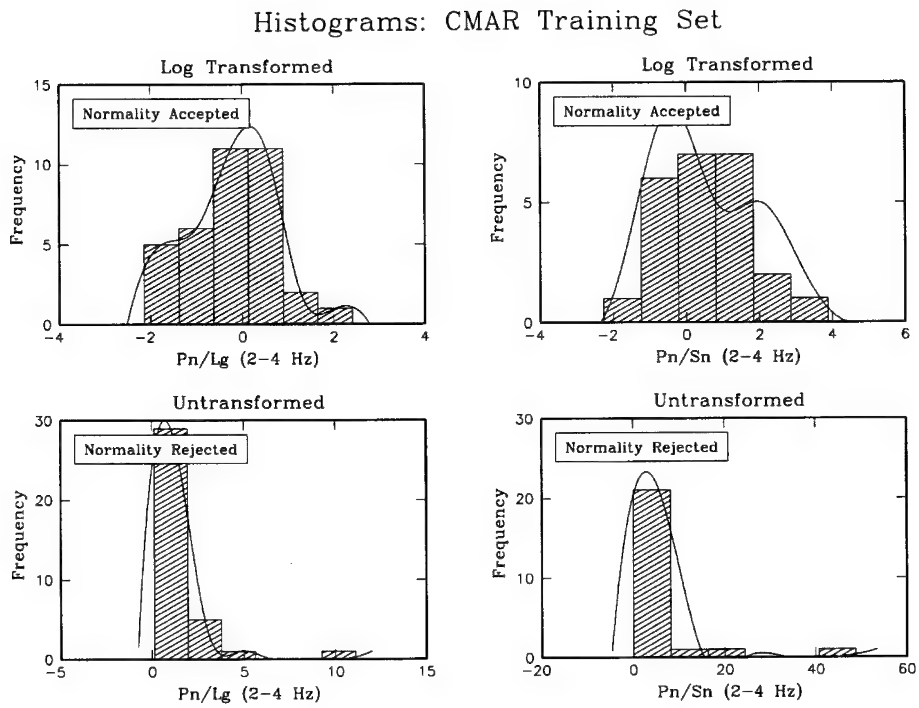

Figure 23. Histograms for CMAR before and after log transformation for Pn/Lg and Pn/Sn (2–4 Hz).

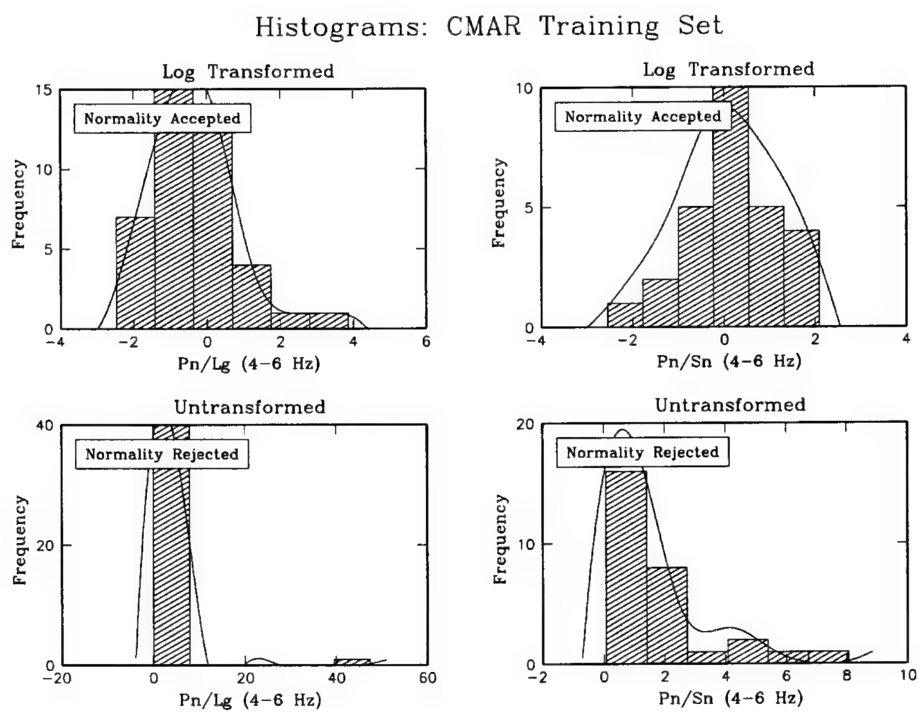

Figure 24. Histograms for CMAR before and after log transformation for Pn/Lg and Pn/Sn (4–6 Hz).

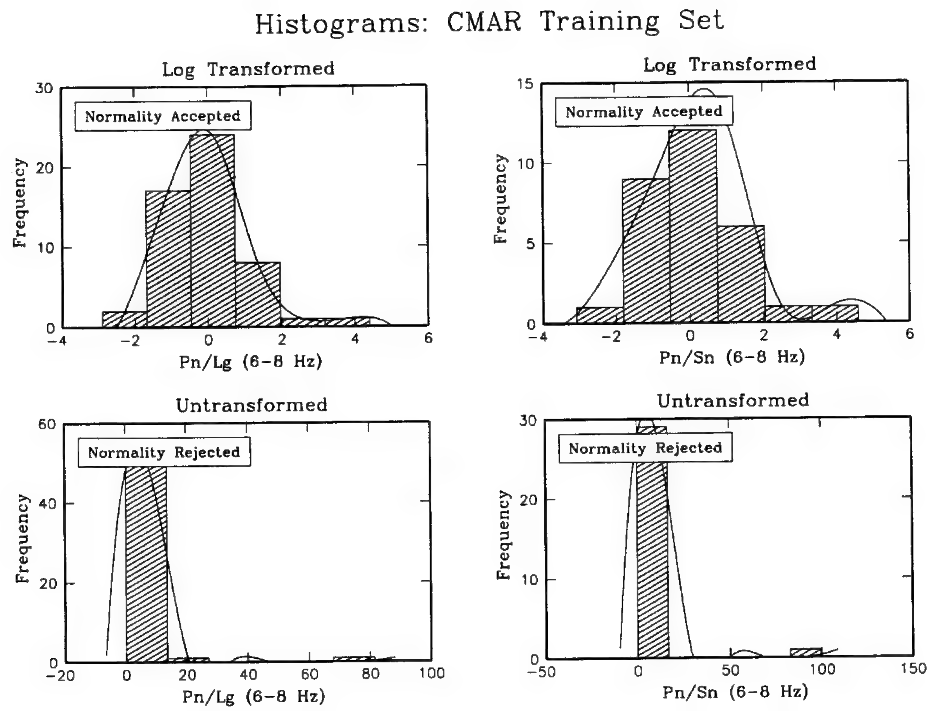

Figure 25. Histograms for CMAR before and after log transformation for Pn/Lg and Pn/Sn (6–8 Hz).

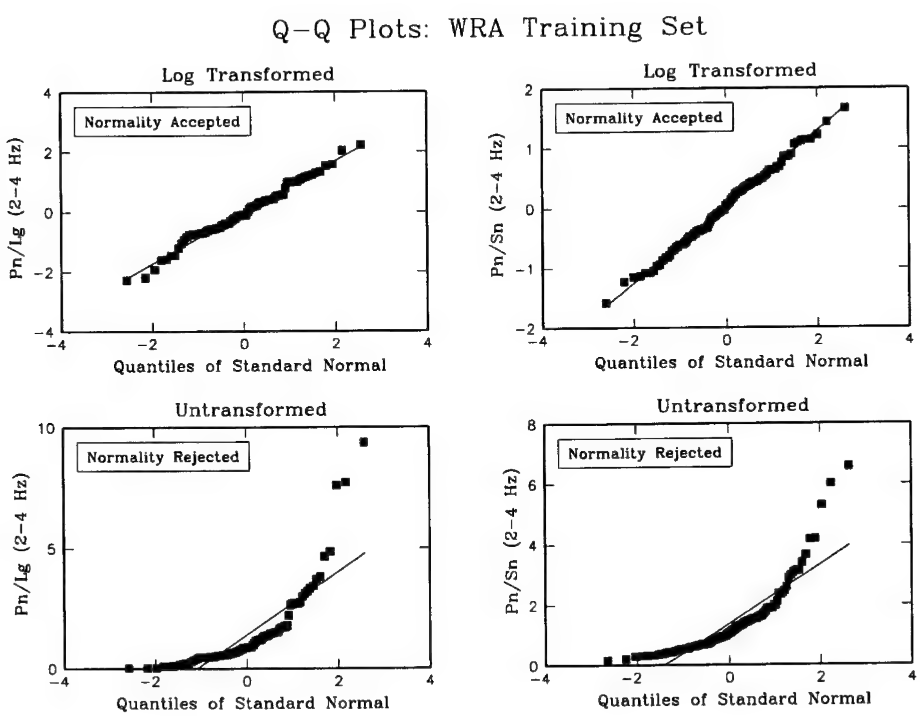

Figure 26. Q-Q plots for WRA before and after log transformation for Pn/Lg and Pn/Sn (2–4 Hz).

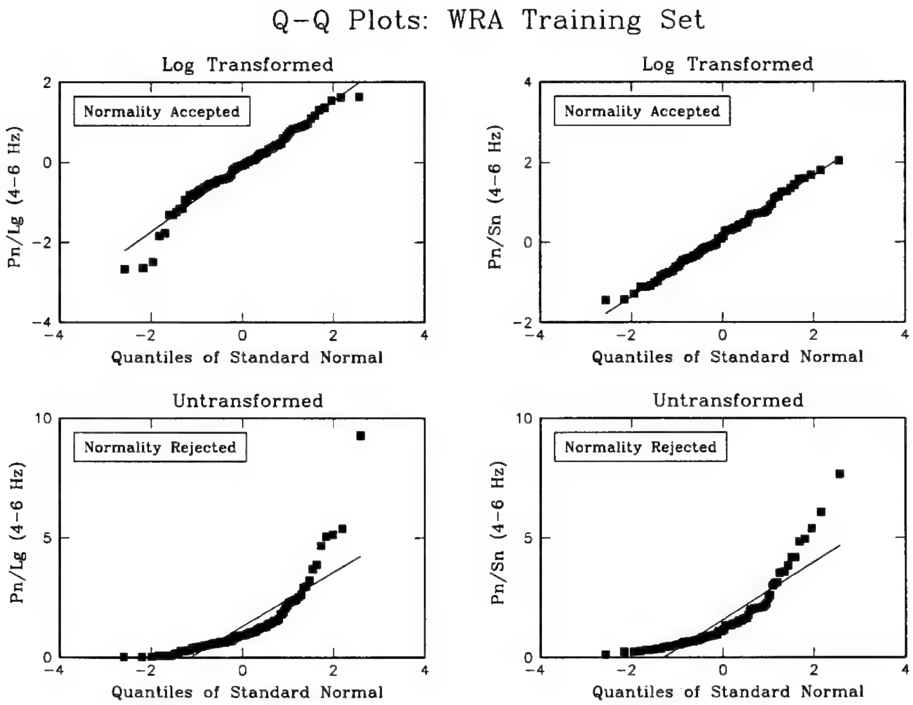

Figure 27. Q-Q plots for WRA before and after log transformation for Pn/Lg and Pn/Sn (4–6 Hz).

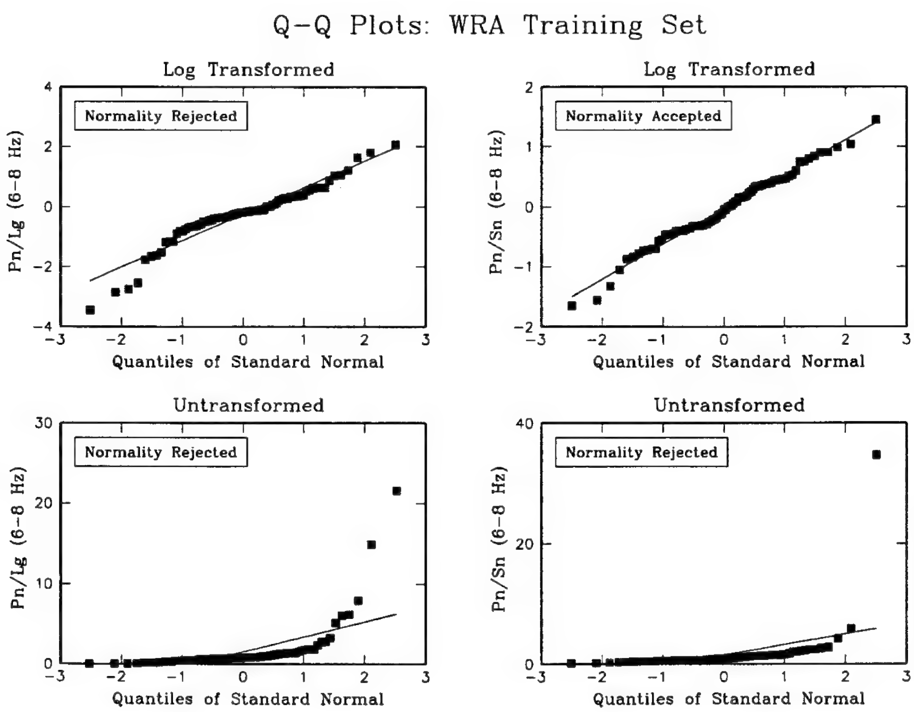

Figure 28. Q-Q plots for WRA before and after log transformation for Pn/Lg and Pn/Sn (6–8 Hz).

For each of the 50 Primary and Auxiliary stations with at least 10 events in the training set, we tested each discriminant data set for normality at the 0.01 significance level both before and after the log transformation. The results are summarized in Tables 3 and 4. For comparison, results for each discriminant using the best Box-Cox transformation are shown in Table 5. Before applying the transformation only about 40% of the discriminant sets are accepted as normal, whereas after applying the log transformation well over 90% of the discriminant sets are accepted as normal. For comparison, if the best Box-Cox transformation is applied to each discriminant individually then almost 99% are accepted as normal. It should be remarked that it is better to not make the log transformation if the original data are accepted as normal because study has shown that the outlier test has greater power for detecting explosions using Pn/Sn and Pn/Lg than using the logarithm of these quantities.

Table 3. Normality test results for discriminants with no transformation.

	# Accepted	# Rejected	# Insufficient
Pn/Lg (2–4 Hz)	21	28	1
Pn/Lg (4–6 Hz)	24	24	2
Pn/Lg (6–8 Hz)	18	29	3
Pn/Sn (2–4 Hz)	19	29	3
Pn/Sn (4–6 Hz)	22	25	3
Pn/Sn (6–8 Hz)	18	26	6
Total	122	161	17

Table 4. Normality test results for discriminants with log transformation.

	# Accepted	# Rejected	# Insufficient
Pn/Lg (2–4 Hz)	47	2	1
Pn/Lg (4–6 Hz)	43	5	2
Pn/Lg (6–8 Hz)	44	3	3
Pn/Sn (2–4 Hz)	47	1	2
Pn/Sn (4–6 Hz)	44	3	3
Pn/Sn (6–8 Hz)	39	5	6
Total	264	19	17

Table 5. Normality test results for discriminants with Box-Cox transformation.

	# Accepted	# Rejected	# Insufficient
Pn/Lg (2–4 Hz)	49	0	1
Pn/Lg (4–6 Hz)	47	1	2
Pn/Lg (6–8 Hz)	47	0	3
Pn/Sn (2–4 Hz)	48	0	2
Pn/Sn (4–6 Hz)	47	0	3
Pn/Sn (6–8 Hz)	42	2	6
Total	280	3	17

5.2. Iterative Procedure to Remove Outliers

Once distance corrections and transformations to normality have been made, each training set, in principle, consists of samples from the same normal earthquake population, with the exception of, at most, a small number of events. These may be events of other types, such as explosions or large mining blasts, or earthquakes for which there is some type of anomalous measurement. If we test for outliers at 0.01 significance level then, on average, one legitimate event in a training set of size 100 will be considered an outlier. It is not clear that such events should be removed from the training set, unless there is convincing evidence that the *anomalous* events in question truly do not belong to their respective regional populations. However, for the purpose of refining the distance corrections, we do remove all events with P-values less than 0.005 (from sets of size, e.g., 100), since outliers can potentially alter the estimates of the distance corrections in an adverse way.

To remove outliers from a data set we use the *leave-one-out* procedure. That is, we extract each event from the training set, one by one, and test it as an outlier relative to the remaining events in the set. If the P-value is less than 0.005, that event is removed. After removing all the outliers in this manner, the training set will be somewhat different than before removal and may yield a different set of distance corrections. In this case we use an iterative procedure. With the remaining elements in the training set, a new set of straight lines are fitted to the discriminant data as in Section 3. The individual discriminants are tested for normality and transformed if normality is rejected. Once the new distance corrections and log transformation, if necessary, have been applied, outliers are once again removed using the leave-one-out procedure. We continue with the iteration until there are no events remaining in the set with P-values less than 0.005. Typically this procedure takes one or two iterations when the log transformation is used. In the next section on station categorization we present the number of outliers removed from each of the data sets for each Primary and Auxiliary station.

6. Station Categorization

We now define four categories that describe, in a relatively objective manner, the *operational* status of the initial training sets for each Primary and Auxiliary station in the existing IMS network, for use in experimental evaluation of event characterization capabilities at the PIDC. The categories are in decreasing order of *operational* utility for the regional population analysis, with Category 1 the most useful and Category 4 the least useful. Only Category 1 and Category 2 training sets are currently used in the regional population analysis being performed on a routine basis at the PIDC. (Other criteria, such as a measure of the residuals to the distance corrections, could also be used in quantifying the status of the training sets.)

Category 1:

1. There are 20 or more events with at least one discriminant with SNR > 1.5.
2. The ratio of the distances for the farthest and closest events is > 2.
3. All six estimated slopes are > 0 and < 3.

Category 2:

1. There are 20 or more events with at least one discriminant with SNR > 1.5.
2. The ratio of the distances from the farthest event to the closest event is < 2.
3. Estimated slopes can have any value.

Category 3:

1. There are 20 or more events with at least one discriminant with SNR > 1.5.
2. The ratio of the distances for the farthest and closest events is > 2.
3. At least one estimated slope is < 0 or > 3.

Category 4:

1. There are less than 20 events with at least one discriminant with SNR > 1.5.

Clearly as more data becomes available there will be fewer stations in Category 4. Category 1 stations were described in detail in Section 3. Category 2 stations have all events in the training set closely spaced. We use as the definition of close, $\Delta max/\Delta min < 2$, where Δmax is the distance of the event farthest from the station and Δmin is the distance of the event closest to the station. This definition is equivalent to the difference in the farthest event and the closest on the log plot being equal to the constant $\log_{10} 2 = 0.3$. If most events are close to the same distance, then distance corrections are not nearly as important since all events will be corrected by roughly the same

amount, whether accurate or not. All events in Category 3 have at least one slope of a suspicious character requiring further, more detailed, study to determine if simple distance corrections are adequate to correct discriminant values for events at different locations.

Tables 6 and 7 list each Primary and Auxiliary station, respectively, in Category 1. Similarly Tables 8 and 9 list the stations in Category 2, Tables 10 and 11 list the stations in Category 3, and Tables 12 and 13 list the stations in Category 4.

Table 6. Category 1 Primary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
CMAR	1	87	47	246	2220	0
CPUP	1	30	11	724	2222	1
ESDC	1	35	15	273	2218	2
GERES	1	161	82	323	2221	8
ILAR	1	85	75	163	2201	3
KSAR	1	141	89	159	2215	0
MJAR	1	175	74	138	2209	10
NORES	1	38	14	435	2167	1
PDY	1	24	19	372	2163	0

Table 7. Category 1 Auxiliary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
AFI	1	25	17	144	1572	0
BBB	1	27	21	212	1981	0
DAVOS	1	95	55	235	2179	1
HFS	1	31	10	569	2147	1
HNR	1	45	27	139	2212	0
INK	1	59	46	368	2211	1
KKJ	1	80	35	278	2199	3
OGS	1	54	40	147	2181	3
SPITS	1	40	32	180	2158	0
VRAC	1	39	24	265	2107	4

Table 8. Category 2 Primary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
ASAR	2	137	58	1174	2220	1
WRA	2	263	163	1265	2213	13

Table 9. Category 2 Auxiliary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
CTA	2	78	22	1137	2221	2
MBC	2	27	19	1335	2169	0

Table 10. Category 3 Primary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
ARCES	3	34	24	329	2132	1
BJT	3	20	3	847	2127	0
FINES	3	34	13	425	2207	1
LOR	3	60	40	461	1958	7
LPAZ	3	39	22	353	2216	0
PDAR	3	33	10	284	2099	3
PLCA	3	22	13	392	1859	0
TXAR	3	45	29	946	2192	0
YKA	3	32	24	785	2206	0
ZAL	3	53	10	496	2217	2

Table 11. Category 3 Auxiliary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
ALQ	3	28	8	852	2178	0
DLBC	3	54	37	617	2212	0
EKA	3	56	37	800	2216	1
JER	3	21	18	326	2114	0
KVAR	3	30	13	256	2217	0
NEW	3	21	3	768	2182	1
NIL	3	45	17	270	2139	2
PMG	3	70	50	280	2001	0
SHK	3	65	44	281	2032	3
SNZO	3	30	24	167	2134	0

Table 12. Category 4 Primary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
ABKT	4	16	7	408	2015	2
BDFB	4	0	0	N/A	N/A	N/A
BGCA	4	2	1	1156	2095	0
BOSA	4	14	11	236	2106	1
DBIC	4	12	4	1198	1733	0
HIA	4	0	0	N/A	N/A	N/A
KBZ	4	9	3	292	2005	0
MAW	4	0	0	N/A	N/A	N/A
MNV	4	19	12	458	1809	0
NRI	4	2	1	1772	1827	0
SCHQ	4	4	1	1294	2158	0
STKA	4	3	0	2036	2220	0
ULM	4	6	1	913	2182	0
VNDA	4	0	0	N/A	N/A	N/A

Table 13. Category 4 Auxiliary Stations.

Station	Category	# Events (SNR > 1.5)	# Events (SNR > 2.0)	Δmin	Δmax	# Outliers
AAE	4	0	0	N/A	N/A	N/A
AQU	4	0	0	N/A	N/A	N/A
ARU	4	4	2	1779	2189	0
BORG	4	3	1	198	1854	0
DAV	4	6	2	552	1416	0
ELK	4	18	11	380	1762	0
FITZ	4	15	6	1310	2162	0
FRB	4	1	0	1297	1297	0
ISG	4	18	7	67	1321	0
JTS	4	0	0	N/A	N/A	N/A
KIEV	4	12	8	438	1828	0
LSZ	4	0	0	N/A	N/A	N/A
MLR	4	0	0	N/A	N/A	N/A
MSEY	4	0	0	N/A	N/A	N/A
NNA	4	13	10	353	2083	0
NWAO	4	3	2	1848	1990	0
OBN	4	18	5	1602	2192	0
PFO	4	17	11	283	1594	0
PTGA	4	0	0	N/A	N/A	N/A
RAR	4	12	5	1399	2152	0
RPN	4	0	0	N/A	N/A	N/A
SADO	4	2	1	929	1439	0
SDV	4	0	0	N/A	N/A	N/A
SFJ	4	1	0	2028	2028	0
SUR	4	3	3	711	909	0
TKL	4	1	1	1889	1889	0
TSUM	4	3	2	878	1279	0
ULN	4	12	10	716	2149	0

Each table contains the number of events measured with at least one discriminant with SNR > 1.5, used to determine the category, as well as the number of events with SNR > 2.0, for future considerations. In addition, each table lists the distance of the event farthest from the station, Δmax, and the distance of the event closest to the station, Δmin, both in kilometers. The last column contains the number of outliers, determined by the methods of Section 5, that have been removed from the training set for that station.

Figures 29 shows each Primary station located on a map of the world. Category 1 stations are depicted by green squares, Category 2 stations are depicted by yellow triangles, Category 3 stations are depicted by orange diamonds, and Category 4 stations are depicted by red circles. Figure 30 is a similar plot for Auxiliary stations.

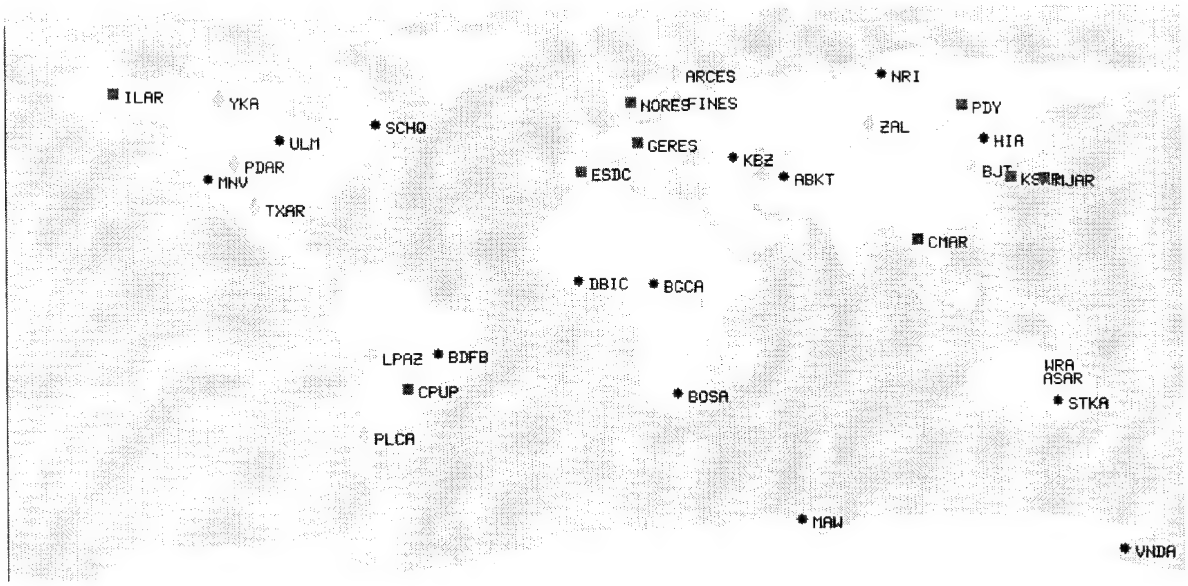

Figure 29. **Locations of Primary seismic stations: Category 1 - green squares, Category 2 - yellow triangles, Category 3 - orange diamonds, Category 4 - red circles.**

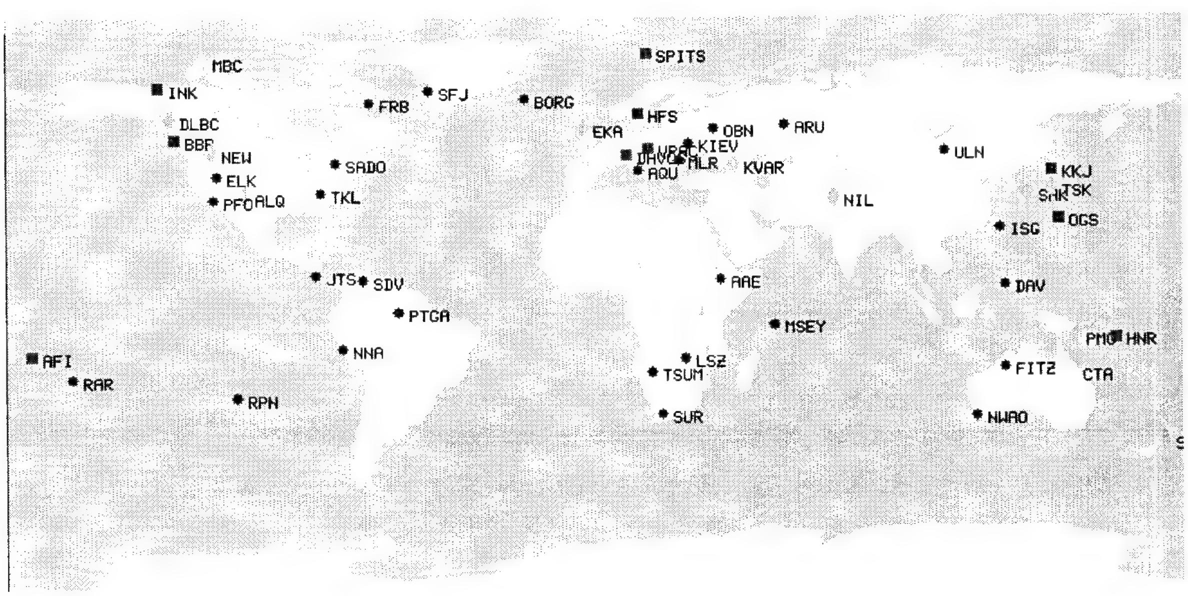

Figure 30. **Same as Figure 29, but for the Auxiliary seismic stations.**

7. Conclusions and Recommendations

In this report we have described initial efforts to establish training sets of regional seismic data for use in the regional population (i.e., outlier) analysis. Each Primary and Auxiliary seismic station in the existing IMS network has been categorized in a manner which qualitatively describes the utility of these initial training sets for the outlier analysis, in terms of the number of events with regional amplitude ratios satisfying an SNR criterion and with *reasonable* distance corrections. At this time, Category 1 and Category 2 stations, listed in Tables 6–9, are being used for preliminary experimental evaluation of event characterization capabilities at the prototype IDC.

Category 3 stations, not recommended for use at this time, all contain at least one discriminant with an unusual dependence on distance from the station. Our current "prejudice" is that the discriminant ratios, Pn/Lg and Pn/Sn in the 2–4 Hz, 4–6 Hz, and 6–8 Hz bands, should typically be increasing functions of distance which can be approximated by a power-law relation, as in Eq. (1) (straight lines in log-log plots), with exponent positive and not too large (less than three). We are currently conducting studies to decide what one should think about some of the unexpected results we have obtained by fitting Eq. (1) to the IMS data.

It may be that the accumulation of sufficient data, or further theoretical understanding, will show that some of the unexpected slopes are actually what should be expected. In such cases, some of the Category 3 training sets could be included in Category 1 without the restrictions on the slopes.

On the other hand, it may be the case that other variables, such as the direction from the station (i.e., azimuth), radiation pattern effects and tectonic characteristics of the propagation path, influence the statistical distribution of regional discriminants and must be taken into account. A first step in addressing such possibilities is a detailed study of the dependence of the discriminant values on these variables, in conjunction with distance from the station. Hopefully, such a study would suggest ways to correct the data using all these variables, such as using multivariate regression, or ways to break regions around some stations into tectonic subregions. This will require more regional data, amounts of which are now steadily increasing at the PIDC.

For example, Figure 31 shows a tectonic grid, with 2 by 2 degree resolution, that was established by Oli Guudmundsson and provided to us by Sereno and Jenkins of SAIC. Figure 32 shows an enlarged view of the tectonic grid for the region surrounding Australia, with regional events (including those below mb 3.5) detected by ASAR and WRA depicted by the circular markers. Most of the regional events depicted in Figure 32 occurred in the tectonically-active subregion near Indonesia. Figure 32 illustrates how a region surrounding a given station could be divided

into tectonic subregions so that training sets for the regional population analysis could also be split into corresponding subregions, whereby a new event is compared to only those training events that occurred in the same subregion. Jenkins et al. (1996) have previously considered the use of this grid in establishing attenuation corrections for distinct tectonic subregions.

Regardless of how the studies on the distance corrections turn out, we are interested in the possibility that valid application of the outlier test can be performed by using a training set containing only those events which are close in relative distance as the test event, so that distance corrections need not be made. In the current method of analyzing discriminants, "close" would mean having a similar distance from the station. A better definition of "close" would require all training events to be within a certain distance of the test event, which would require much more data so as to have enough training events at roughly the same location. In either case, it is a non-trivial problem to quantify the notion of close. Basically, it must be determined if it is better to include a potential training event at a given distance away from the test event than to not include it in the set. This, of course, depends on how much different the distribution of events at the further location is than the events at the test event location. If this were known, then a correction could be made; however, the point is that, in these cases, the dependence on distance is not known and it is often difficult to approximate. Thus, the problems of determining the dependence of discriminant distributions on location and what is meant by close are intimately related.

To illustrate the feasibility of this approach, Figures 33 and 34 show cumulative histograms of the number of events within a log distance range from each station of log 1.5, with a common set of discriminants (Figure 33), and with at least one common discriminant (Figure 34). Events from all of the stations were combined in generating these plots. Figure 33 illustrates that, on average, roughly 30% of the regional events have at least 20 events seen at the same station within the specified distance range and with the same set of regional discriminants. Similarly, Figure 34 illustrates that, on average, roughly 70% of the regional events have at least 20 events seen at the same station within the specified distance range and with at least one common regional discriminant. As more regional data accumulate over time, these percentages should increase proportionately. Thus, this suggests that after a sufficient period of time, e.g., three or more years, there may be a sufficient number of events over a broad enough range of regional distances at many IMS stations to allow direct comparison of events to training events at equivalent distances to the same station. This could alleviate the need apply distance corrections in many cases.

Each of the studies discussed above is worthy of further research and we plan to pursue each in the near future. In addition, we plan to make continued iterative improvements to the existing regional distance corrections and training sets as more data are collected at the PIDC.

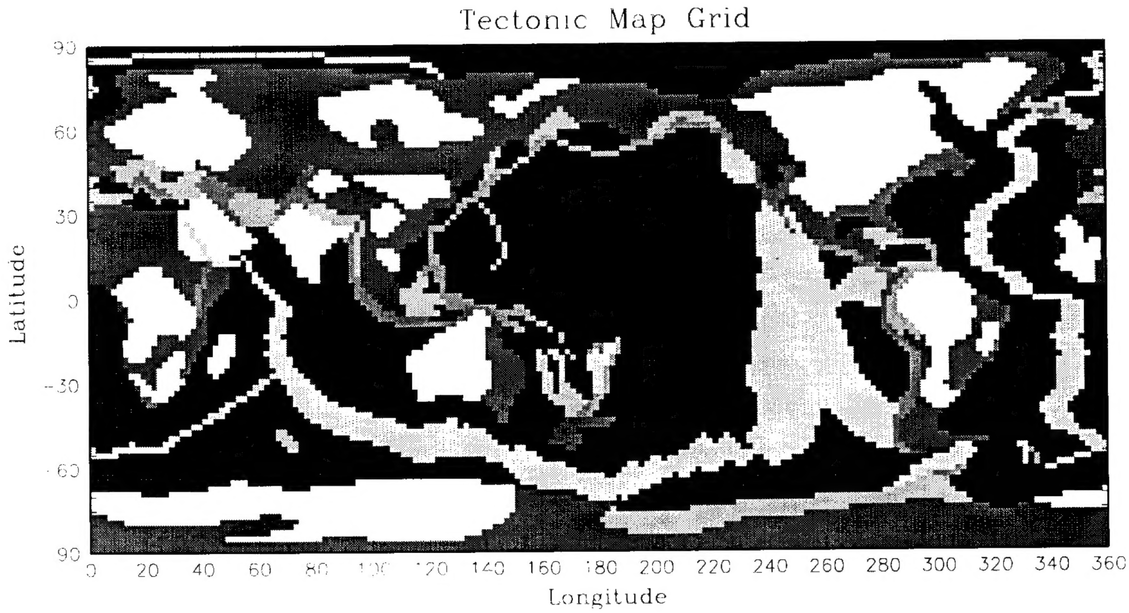

Figure 31. **Tectonic grid of the world, with 2 by 2 degree resolution, established by Oli Guudmundsson.**

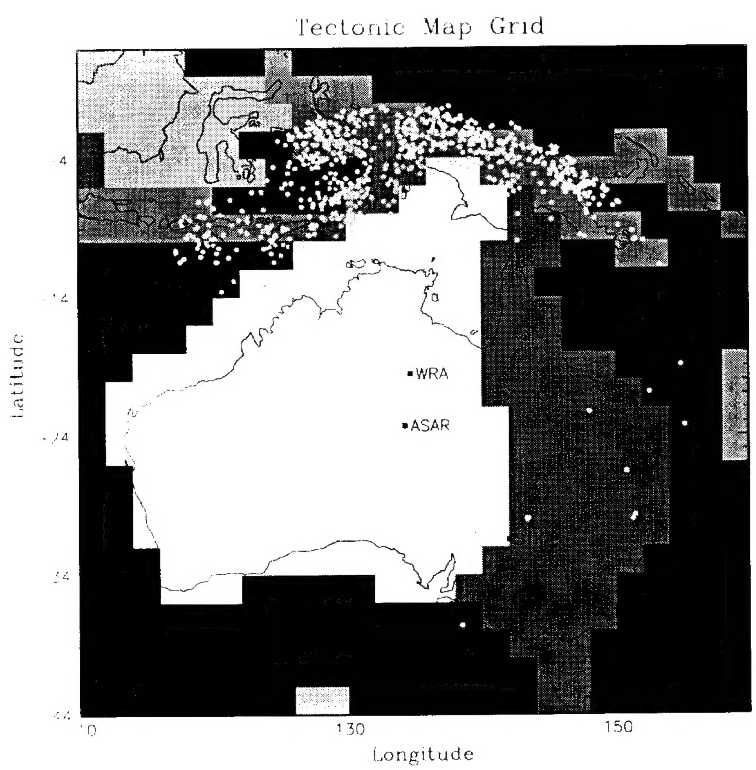

Figure 32. **Enlarged view of the tectonic grid for the region surrounding Australia, with regional events detected by ASAR and WRA depicted by the circular markers.**

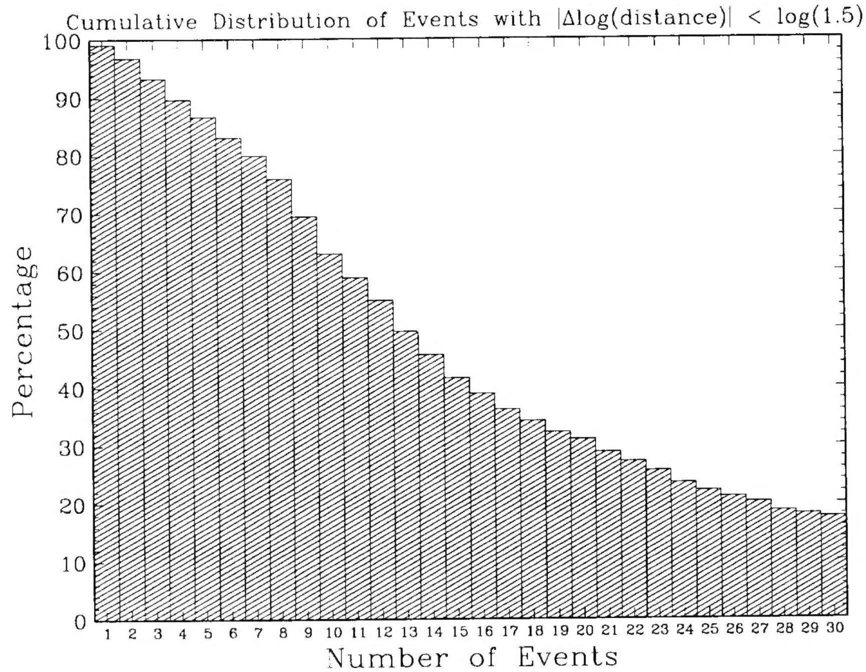

Figure 33. Cumulative histogram of events within a log distance range of log 1.5 and with a common full set of discriminants.

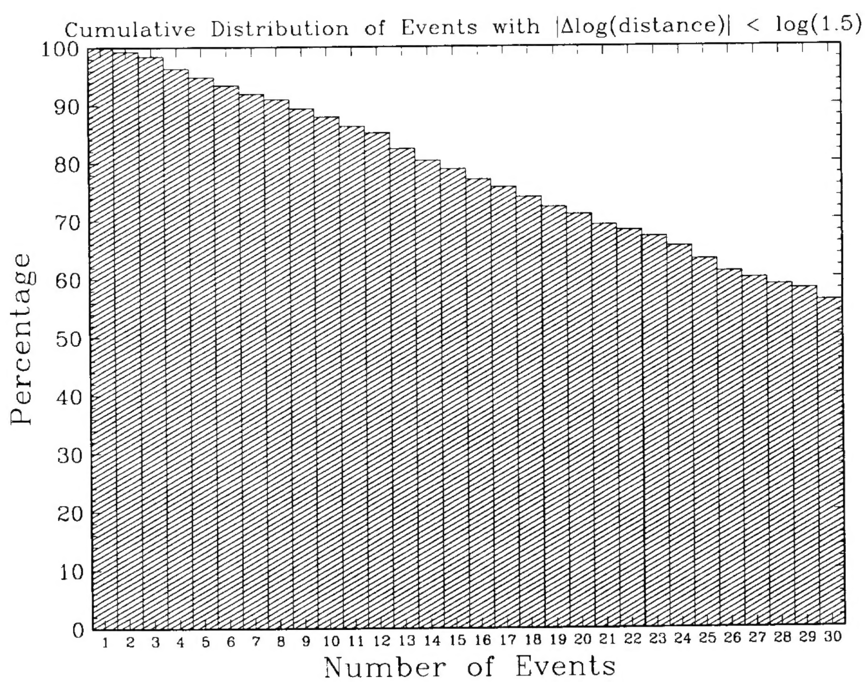

Figure 34. Cumulative histogram of events within a log distance range of log 1.5 and with at least one discriminant in common.

8. References

Anderson, T. W. and D. A. Darling (1954). A test of goodness-of-fit, *J. Am. Stat. Assoc.*, **49**, 765–769.

Baumgardt, D., and Z. Der (1994). Investigation of the Transportability of the P/S Ratio Discriminant to Different Tectonic Regions, PL-TR-94-2299, Phillips Laboratory, Hanscom AFB, MA, ADA292944.

Box, G. E. P. and D. R. Cox (1964). An analysis of transformations, *J. R. Stat. Soc.*, **26**, 211–252.

Fisk, M. D., R. J. Carlson, V. Burlacu and G. D. McCartor (1996a). Interactive World Wide Web Pages for Custom Event Screening at the Prototype International Data Center, PL-TR-96-2269, Phillips Laboratory, Hanscom AFB, MA, ADA322284.

Fisk, M. D., H. L. Gray and G. D. McCartor (1996b). Regional event discrimination without transporting thresholds, *Bull. Seis. Soc. Am.*, **86**, 1545-1558.

Fisk, M. D., H. L. Gray and G. D. McCartor (1995). Statistical Methodology and Assessment of Seismic Event Characterization Capability, PL-TR-95-2156, Phillips Laboratory, Hanscom AFB, MA, ADA305487.

Fisk, M. D., H. L. Gray and G. D. McCartor (1994). Preliminary Assessment of Seismic CTBT/NPT monitoring Capability, PL-TR-94-2300, Phillips Laboratory, Hanscom AFB, MA, ADA293188.

Fisk, M. D., H. L. Gray and G. D. McCartor (1993). Applications of Generalized Likelihood Ratio Tests to Seismic Event Identification, PL-TR-93-2221, Phillips Laboratory, Hanscom AFB, MA, ADA279479.

IDC Performance Report, December 15, 1997 – January 11, 1997 (28 January 1997). Available through the Prototype Comprehensive Test Ban Treaty (CTBT) International Data Center (IDC) Library, Arlington, VA.

Jenkins, R. D., A. A. Velasco, D. J. Williams and T. J. Sereno (1996). Regional Attenuation at GSETT-3 Stations and the Transportability of the Lg/P Discriminant, PL-TR-96-2159, Phillips Laboratory, Hanscom AFB, MA, ADA317380.

Kennett, B. L. N. (1992). The Distance Dependence of Regional Phase Discriminants, PL-TR-92-2324, Phillips Laboratory, Hanscom AFB, MA, ADA261730.

Kennett, B. L. N. (1991). The Distance Dependence of Regional Phase Discriminants, PL-TR-91-2250, Phillips Laboratory, Hanscom AFB, MA, ADA247546.

Lin, C.-C. and G. S. Mudholkar (1980). A simple test for normality against asymmetric alternatives, *Biometrika*, **67**, 455–461.

Sereno, T. J., (1990). Attenuation of Regional Phases in Fennoscandia and Estimates of Arrival Time and Azimuth Uncertainty using Data Recorded by Regional Arrays, SAIC-90/1472, Science Applications International Corporation, San Diego, CA.

Shapiro, S. S. and M. B. Wilk (1965). An analysis-of-variance test for normality (complete samples), *Biometrika*, **52**, 591–611.

DEFENSE TECHNICAL INFORMATION CENTER
8725 JOHN J. KINGMAN ROAD
FORT BELVOIR, VA 22060-6218 (2 COPIES)

PHILLIPS LABORATORY
ATTN:PL/SUL
3550 ABERDEEN AVE SE
KIRTLAND, NM 87117-5776 (2 COPIES)

DEFENSE SPECIAL WEAPONS AGENCY
ATTN: PMP
6801 TELEGRAPH ROAD
ALEXANDRIA, VA 22310-3398

PHILLIPS LABORATORY
ATTN: GPBP
29 RANDOLPH ROAD
HANSCOM AFB, MA 01731-3010

PHILLIPS LABORATORY
ATTN: TSML
5 WRIGHT STREET
HANSCOM AFB, MA 01731-3004

MARK D. FISK
MISSION RESEARCH CORPORATION
735 STATE STREET
P.O. DRAWER 719
SANTA BARBARA, CA 93102-0719 (5 COPIES)